Florida Value-Added Model Technical Report

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FLORIDA VALUE-ADDED MODEL

INTRODUCTION

The State of Florida has committed to using value-added methods as a component of its teacher evaluation system as required by the Student Success Act (Senate Bill 736) as well as its Race to the Top proposal (RTTT). The value-added model (VAM) described in this technical report is applied to the Florida Comprehensive Assessment Test (FCAT) in reading and mathematics across grades 3 through 10. Other models using data from different sources, such as End-of-Course assessments, will be developed in subsequent work.

In 2011, the Florida Legislature passed Senate Bill 736, which was also closely aligned with the objectives for teacher evaluation as proposed in the state's RTTT application. The Act and the RTTT application both require the use of student achievement test score data as one element of a teacher evaluation system. The role of the VAM is to differentiate teacher performance by using statistical models to measure student learning growth and attribute this growth to specific teachers. It accomplishes this by making use of Florida's longitudinal test score data from the FCAT.

The State enlisted a diverse group of stakeholders, referred to as the Student Growth Implementation Committee (SGIC), to serve as an evaluation committee and to make final recommendations as to the specific value added model that is best suited to the needs of teachers and students across the state. The members of the SGIC include teachers, principals, parents, union representatives, superintendents, school board members, district administrators, and postsecondary faculty who contribute expertise in various teaching subjects and grades, educational administration at all levels, and in the areas of measurement and assessment. The names and affiliations of the SGIC members are provided in Appendix A.

This committee convened twice in Orlando, Florida and held approximately four phone conferences with the Florida Department of Education and the contracted vendor, the American Institutes for Research (AIR), to consider advantages and disadvantages of different modeling approaches that have been proposed in the value-added literature. Based on SGIC recommendations, AIR implemented over 120 different VAMs, which were subsequently reviewed and compared by the SGIC.

Based on the SGIC's review of the results across the array of models, a specific model was recommended to the State Commissioner of Education. The committee's recommended model was selected by the Commissioner and will become the model used operationally for the FCAT reading and math tests to support SB 736 and all RTTT activities.

This technical report describes the value-added model selected by the SGIC and the Commissioner and provides summaries of its results. The complete technical and computational details of the model are provided as well as a summary of its results. The report is organized to provide some context on different modeling approaches that were presented to the SGIC.

A more comprehensive description of different value-added modeling techniques and how these different approaches relate to each other can be found in McCaffrey, Lockwood, Koretz, Louis, and Hamilton et al (2004).

Value-Added Modeling

Value-added modeling with educational test score data is the process of statistically analyzing student level test scores collected over a period of time with the intent of separating factors unique to students and schools from factors unique to a classroom teacher to attribute growth in student achievement to teachers and schools. The factor unique to a teacher is typically referred to as a *teacher effect* and is thought to be the causal impact of the teacher's instructional efficacy on the student's achievement as reflected via the test scores.

All VAMs have similar aims, but use different assumptions and principles. McCaffrey et al. (2004) have demonstrated the relationship across commonly used VAM approaches, showing how different models can be viewed as special cases of a more general longitudinal model. Nonetheless, it is fair to characterize VAMs as falling into two modeling categories: those which we refer to as *learning path models* (typically referred to as variable persistence in the literature) and *covariate adjustment models*. These are described briefly below.

Two Common Value-Added Designs

All value-added models use longitudinal, student-level data. However, various models make use of the data in different ways. For instance, the variable persistence model (McCaffrey et al, 2004) uses the student level data as the vector of outcomes in a mixed linear regression and makes assumptions about how prior year teachers contribute to current year learning gains. Such an approach implicitly assumes all students have a predetermined learning trajectory relative to the mean outcomes in the state and that current year teachers can alter that trajectory upwards with good instruction or downwards with less effective instruction.

Covariate adjustment models use the longitudinal data somewhat differently. In these models, the current year test score alone serves as the outcome in a linear regression and the prior year scores are used as conditioning variables. The models assume that students with a teacher of average effectiveness will score similar to other students with similar prior test scores and other characteristics. A teacher with a positive impact will alter the student's current year outcome in a way such that the student performs better than is predicted, and a teacher with negative impact will affect the outcome such that the student does not perform as well as predicted.

In either case, the outcomes across different subject areas (e.g., reading and math) can be modeled marginally—a separate regression for math and another for reading or jointly—where reading and math scores are simultaneously used as outcomes in a regression. Accommodating the latter approach presents additional computational challenge, requiring a slight difference in the parameterization of the within-student covariance matrix to account for correlation across error terms across the different tests.

However, Lockwood, McCaffrey, Mariano, and Setodji (2007) have shown that modeling the outcomes jointly has only very modest effects on estimates of value added. They show that the estimated teacher effects from a joint and marginal model were correlated greater than .99. The conditional variances of the teacher effects were also shown to differ only by nominal amounts.

There is one additional characteristic of the variable persistence model that does not appear in the covariate adjustment design—the impact of prior year teachers on current year outcomes.

There are essentially two competing approaches on how to treat prior year teachers. One assumes complete persistence, meaning that the impact of a prior teacher on current outcomes does not dissipate at all (Ballou, Sanders, Wright, 2004). In other words, the impact that prior teachers had on the students learning path perpetually remains with that student. This implies that prior teachers have permanently impacted student learning paths.

A separate approach assumes that the impact of the prior teacher is an additional parameter of the model and it should be estimated from the data (McCaffrey et al, 2004). In most cases, the impact of the prior teacher diminishes in some fashion, meaning that the impact of prior year teachers most likely declines with students over time. Under these assumptions, the fact that last year's teacher had a large impact on the student's learning path does not mean that the student's learning path is forever altered by that teacher as is assumed with complete persistence.

One additional issue that affects covariate adjustment models that has a significant impact on the model results is the impact of measurement error in the predictor variables. It is well established that conditioning on variables measured with error yields bias in the model parameters (Greene, 2000). Some approaches use an instrumental variables (IV) approach (Meyer, 1992). The use of IV is typically used when one of the predictor variables is correlated with the error term in the regression model—a situation which occurs when predictor variables are measured with error. However, there are challenges in identifying what to use as useful instruments. Ignoring this error in high stakes accountability systems yields results that are subject to much criticism and should be accounted for.

The Florida Value-Added Model

The model implemented for the State of Florida is a covariate adjustment model that includes two prior test scores as predictor variables (except in grade 4 where only one predictor is available), a set of measured characteristics for students, with teachers and schools treated as coming from a distribution of random effects. The model is an error-in-variables regression to account for the measurement error in the predictor variables used. A complete technical description of the model is found in the Methods section of this report.

The predictor variables used in the model are the same across all grades in both reading and math, and they are:

- The number of subject-relevant courses in which the student is enrolled: Some students are enrolled in multiple courses that, according to the Florida course code directory, are linked to an FCAT test. This variable counts, for each student, the number of courses they are enrolled in that is linked to the FCAT test via the course code directory (see Appendix B).
- Two prior years of achievement scores: These are always the scores for the subject from the two prior years. For example, grade 8 math uses grades 6 and 7 FCAT math scores as predictors.
- Disabilities (SWD) status: This is a dichotomous variable denoting whether a student receives special education services for a specific disability.

- English language learner (ELL) status: This is a dichotomous variable denoting whether students are currently enrolled in an English language learner program or not for less than two years.
- Gifted status: This is a dichotomous variable denoting if the student is enrolled in a gifted program or not.
- Attendance: This is a continuous variable counting the number of days the student was present during the school year.
- Mobility (number of transitions). This is a continuous variable counting the number of transitions across schools within the same school year.[*]
- Difference from modal age in grade (as an indicator of retention): This is a continuous variable computed as $x_i - x$ where x_i is the age in months for student *i* and *x* is the modal age for students enrolled in the same grade across the state.
- Class size: A continuous measure counting the number of students linked to teacher j.
- Homogeneity of entering test scores in the class: A continuous variable computed as the interquartile range of student entering scores in the class.

Certain properties of the FCAT scale caused for some concern over its proposed interval nature. The FCAT reports what is referred to as a developmental scaled score (DSS), which is a vertical scale measuring achievement across all grades. However, disparate patterns of growth in different grades suggest gain scores may not be comparable in different grades. For instance, we observe much larger growth estimates for grade 4 students than other grades, especially in reading.

One possible consequence of this disparate pattern is that teachers in lower grades could appear to have larger value-added estimates relative to teachers in higher grades if all teachers were included in the same analysis. There are many possible ways to address this concern, some of which can be model-based (i.e., parameterize the model to account for these differences) or run separate models for each grade. We chose the latter to address this concern.

Attribution of School Component to Teacher Effect

The VAM applied to the FCAT data decomposes total variation in achievement into three orthogonal components: variation between schools, variation between teachers within a school, and variance between students within a classroom. The parameterization of the model forms what is commonly referred to as a hierarchical linear model (HLM)[†].

While all parameters are estimated simultaneously, it is useful to consider the levels separately. First, student-level prior test scores (i.e., the lags) and the covariates are used to establish a

[*] The 2010-11 model does not include the attendance or mobility covariates because the data was not available from the FLDOE at the time of the analysis; these covariates will be included and results provided to the state in late fall 2011.

[†] The model does link some students into different classrooms given the linkages derived from the course code catalog. Consequently students are not always linked to one and only one teacher. It is therefore more appropriate to refer to this model as having crossed random effects

statewide conditional expectation. This expectation is the score a student is expected to have, given his or her prior test score history and measured characteristics.

However, schools exhibit differential amounts of growth. The model cannot differentiate whether these differences are due to independent factors at the school (e.g., particularly effective leadership) or simply due to the sorting of high-growth teachers into some schools rather than others. We refer to this as the *common school component* of student growth. The common school component therefore describes the amount of learning that is typical for students in each school that differs from the statewide conditional expectation.

Whether or not to estimate the common school component and teacher effects was a source of significant discussion for the SGIC, and it is a source of significant discussion in the value-added literature. If school effects are ignored and the model includes only teacher effects, then legitimate differences between teachers could be exaggerated as some of the teacher effect includes the common school component. In other words, some teachers could appear to have higher (or lower) value-added than is true in reality as their effect includes things that may be reasonably viewed as out of their immediate control, such as principal leadership. In contrast, if school effects are included, then some of the legitimate differences between teachers could be minimized. In other words, the school effect now captures some of the teacher effect. As a result, when estimating a value-added model, we needed to determine whether the model should:

1. estimate the common school component, thus potentially removing some legitimate differences between teachers; or
2. ignore the common school component and assume that any difference in learning across classes is entirely a function of classroom instruction; or
3. find some middle ground where teacher value-added scores include some but not all of the common school component.

If we subscribe to the notion that some of the school component reflects the sorting of more effective teachers into some schools, then we may wish to apportion some of the school effect back to teachers. However, how much of the school effect gets attributed back to teachers cannot be determined via the value-added model though these decisions have important implications for interpreting teacher value-added scores, particularly across schools. Specifically, if the committee voted to add none of the school component (0%) to teachers' value-added scores there would be one model, but different standards for student outcomes for different schools. Teachers with high-growth in high-growth schools may earn lower value-added scores than teachers with lower growth at a low growth schools.

In contrast, if the committee voted to add all of the school component (100%) to teachers' value-added scores, there would be one model with the same standard for student outcomes, regardless of school. Teachers with high student growth in high growth schools will earn higher value-added scores than teachers with lower growth at low growth schools, regardless of how the teachers' performances compare to their respective schools. After significant discussion, as well as with a second follow-up meeting, the SGIC determined that some of the school effect should be attributed back to teachers. The proportion allocated back was put to vote and agreed upon by the SGIC as 50 percent. Hence, teacher effects are then subject to the following calculation:

*Teacher Value-Added Score = Unique Teacher Component + .50 * Common School Component*

This formula simply recognizes that some of the school component is a result of teacher actions within their schools and that they should receive some credit in their overall value-added effects.

METHODS

Covariate Adjustment Model

The statistical value-added model implemented for the State of Florida is typically referred to as a covariate adjustment model (McCaffrey et al, 2004) as the current year observed score is conditioned on prior levels of student achievement as well as other possible covariates that may be related to the selection of students into classrooms.

In its most general form, the model can be represented as:

$$\mathrm{y}_{ti} = \mathbf{X}_i\boldsymbol{\beta} + \sum_{r=1}^{L} \mathrm{y}_{t-r,i}\gamma_{t-r} + \sum_{q=1}^{Q} \mathbf{Z}_{qi}\boldsymbol{\theta}_q + e_i$$

where y_{ti} is the observed score at time *t* for student i, $\mathbf{X}_i$ is the model matrix for the student and school level demographic variables, $\boldsymbol{\beta}$ is a vector of coefficients capturing the effect of any demographics included in the model, $y_{t-r,i}$ is the observed lag score at time *t-r* ($r \in \{1,2,\ldots,L\}$), $\boldsymbol{\gamma}$ is the coefficient vector capturing the effects of lagged scores, $\mathbf{Z}_{qi}$ is a design matrix with one column for each unit in q ($q \in \{1,2,\ldots,Q\}$) and one row for each student record in the database. The entries in the matrix indicate the association between the test represented in the row and the unit (e.g., school, teacher) represented in the column. We often concatenate the sub-matrices such that $\mathbf{Z} = \{\mathbf{Z}_1,\ldots,\mathbf{Z}_Q\}$. $\boldsymbol{\theta}_q$ is the vector of effects for the units within a level. For example, it might be the vector of school or teacher effects which may be estimated as random or fixed effects. When the vector of effects is treated as random, then we assume $\boldsymbol{\theta}_q \sim N(0, \sigma^2_{\boldsymbol{\theta}_q})$ for each level of q.

Corresponding to $\mathbf{Z} = \{\mathbf{Z}_1,\ldots,\mathbf{Z}_Q\}$, we define $\boldsymbol{\theta}' = (\boldsymbol{\theta}'_1,\ldots,\boldsymbol{\theta}'_Q)$. In the subsequent sections, we use the notation $\boldsymbol{\delta}' = \{\boldsymbol{\beta}',\boldsymbol{\gamma}'\}$, and $\mathbf{W} = \{\mathbf{X},\mathbf{y}_{\mathrm{t-1}},\mathbf{y}_{\mathrm{t-2}},\ldots,\mathbf{y}_{\mathrm{t-L}}\}$ to simplify computation and explanation.

Note that all test scores are measured with error, and that the magnitude of the error varies over the range of test scores. Treating the observed scores as if they were the true scores introduces a bias in the regression and this bias cannot be ignored within the context of a high stakes accountability system. Our approach to incorporating measurement error in the model is described in a later section.

Defining Teacher and School Effects in the Covariate Adjustment Model

The terms teacher and school "effect" imply something causal about the role of teachers and students in the model. While the VAM clearly aims to disentangle factors idiosyncratic to a student and school from a teacher, we truly only have some residual variation at the teacher level

that is then attributed to the classroom teacher as their instructional influence. We retain the use of the term teacher effect because the VAM intends to identify this effect directly. However, the term school effect is not the most appropriate term. Accounting for other factors that are unique to students attending the school does not imply the school itself caused the effect. Instead, including a school component is capturing the latent effect of all potential impacts of the school community, including principal leadership, neighborhood effects, etc. Hence, we prefer the term unique school component for this level.

Because the model is a covariate adjustment model, predictions for students are set for students conditioned on their observed characteristics and prior test scores. That is, the conditional expectation for a student is formally defined as:

$$\begin{aligned} \mathrm{E}(y_{ti}|\mathbf{W}) &= \mathbf{W\delta} \\ &= \hat{y}_{ti} = \mathbf{W}\hat{\boldsymbol{\delta}} \end{aligned}$$

Therefore, the basic idea is to find a conditional expectation for student *i* based on how other students with similar measured characteristics and prior test score have performed. Given the predicted value we then have $r_{ti} = y_{ti} - \hat{y}_{ti}$, which denotes the observed difference between their observed test performance and their predicted performance.

When teachers and schools are treated as random effects, as the SGIC decided to do in Florida value-added model, these residuals are then aggregated for teacher *j* to form the empirical Bayes estimate as:

$$\tilde{\Theta}_{\boldsymbol{j}} = \frac{N_j\sigma_t^2}{N_j(\sigma_s^2+\sigma_t^2)+\sigma_e^2}\frac{\sum_{i=1}^{N_j} r_{(j)i}}{N_j} \qquad \textbf{(1)}$$

where σ_t^2 is the teacher level variance, σ_s^2 is the school level variance, σ_e^2 is the residual variance, N_j denotes the number of students in class *j* and the notation *(j)i* is used to mean that student *i* in class *j*. Equation 1 above is nothing more than the scalar representation of the commonly used matrix notation:

$$\widetilde{\boldsymbol{\Theta}} = \mathbf{DZ'V^{-1}}(\mathbf{y} - \mathbf{W}\boldsymbol{\delta})$$

where $\mathbf{V} = \mathbf{ZDZ'} + \boldsymbol{\Omega}.$ and $\mathbf{V}$ is block-diagonal. However, in Equation 1 we can see that student level residuals form the basis for the quantity referred to as a teacher effect. Hence, given estimates of the model parameters, including the fixed effects and variances of the random effects, we can formally define the teacher effect as the weighted mean of the student level residuals[‡].

Because the estimated teacher effect is a weighted mean of the student level residuals, it is easy to see that a teacher with a positive value-added effect is one whose students, on average, perform better than conditionally expected and a teacher with a negative value added effect is one whose students perform lower than conditionally expected.

[‡] The teacher effect described here is the mathematical description of the empirical Bayes estimate. The “final” teacher effect includes some of the school component added back in. We later show the mathematical construction of the final teacher effect and its variance.

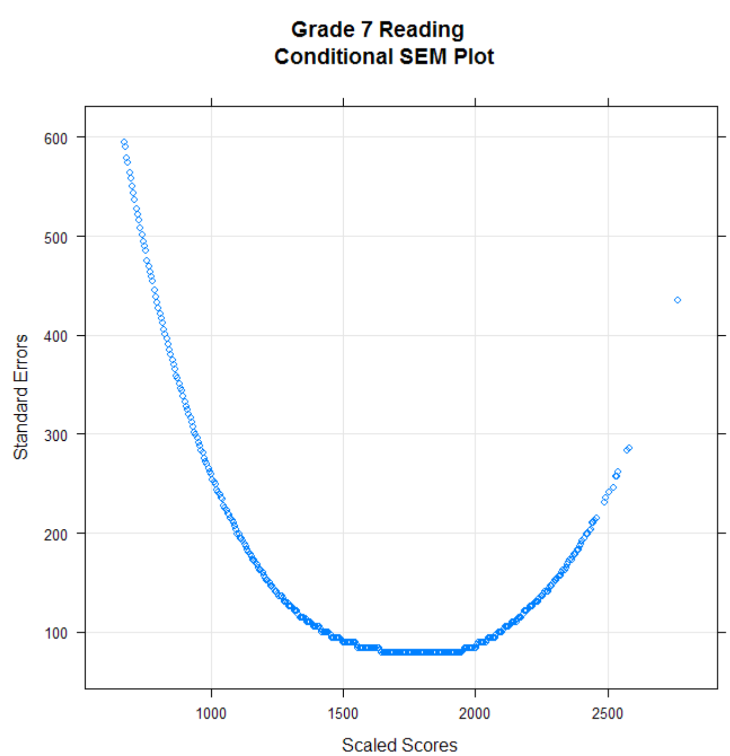
Measurement Error in Educational Achievement Tests and How its Effect Propagates into the VAM

Classical test theory posits that the observed test score is the sum of a true score plus a disturbance, $x = t + e$ and also posits that the observed score variance is the sum of two orthogonal variances, $var(x) = var(t) + var(e)$. From these basic principles, we can define reliability as the ratio of true score variance to the observed score variance, $\rho^2 = var(t)/var(x)$ and also write the classical standard error of measurement as $\sigma_e = \sigma_x(1 - \rho)$. This classical standard error assumes homoscedasticity of the error term across the score range and almost all error-in-variable models are constructed around the classical true score model (Kmenta, 1971).

Item response theory (IRT) extends these basic principles and introduces the concept of the test information function (TIF) (Lord, 1980). Rather than a single index characterizing the precision of the test, the TIF varies along the score continuum providing more information at certain points of the score range. The converse of the TIF, or the lack of information, is taken as the standard error of measurement at a particular score point. Because the TIF varies along the score continuum, so does the standard error of measurement.

In Florida, the conditional standard errors of measurement (CSEM) tend to be larger at the extremes of the score distribution as illustrated in Figure 1. Because there is heteroscedasticity in the error term, the error-in-variables (EiV) regression model must directly take this into account to yield efficient estimates of the model parameters. Our derivation of the EiV model is based on these principles and is described in the next section.

Figure 1



It has been proposed that measurement error in the predictor variables can be ignored when the model conditions on at least three prior test scores (Sanders, 2006). It can, however, be shown analytically as follows that bias will remain, even when multiple scores are used.

Suppose the true score regression is $\boldsymbol{Y} = \boldsymbol{X}^{*}\boldsymbol{\beta} + \boldsymbol{e}$. Let $\boldsymbol{X} = \boldsymbol{X}^{*} + \boldsymbol{U}$ where $\mathbf{U}$ is a matrix of unobserved disturbances with the same dimensions as $\mathbf{X}$. The true score regression is then $\boldsymbol{Y} = (\boldsymbol{X} - \boldsymbol{U})\boldsymbol{\beta} + \boldsymbol{e}$**.** Taking the maximum likelihood estimator for the true regression as

$$\widehat{\boldsymbol{\beta}}_{\text{true}} = (\boldsymbol{X}^{*\prime}\boldsymbol{X}^{*})^{-1}\boldsymbol{X}^{*\prime}\boldsymbol{y}$$

And then upon substitution we have

$$\widehat{\boldsymbol{\beta}}_{\text{true}} = ([\boldsymbol{X} - \boldsymbol{U}]'[\boldsymbol{X} - \boldsymbol{U}])^{-\mathbf{1}}(\boldsymbol{X} - \boldsymbol{U})'\boldsymbol{y}$$

$$= (\boldsymbol{X}'\boldsymbol{X} - \boldsymbol{X}'\boldsymbol{U} - \boldsymbol{U}'\boldsymbol{X} + \boldsymbol{U}'\boldsymbol{U})^{-\mathbf{1}}(\boldsymbol{X}'\boldsymbol{y} - \boldsymbol{U}'\boldsymbol{y})$$

This simplifies because $E(\boldsymbol{X}'\boldsymbol{U}) = E(\boldsymbol{U}'\boldsymbol{X}) = E(\boldsymbol{U}'\boldsymbol{U})$ and $\mathrm{E}(\boldsymbol{U}'\boldsymbol{y}) = 0$. Consequently, $\widehat{\boldsymbol{\beta}}_{\text{true}} = (\boldsymbol{X}'\boldsymbol{X} - E(\boldsymbol{U}'\boldsymbol{U}))^{-\mathbf{1}}\boldsymbol{X}'\boldsymbol{y}$, where as $\widehat{\boldsymbol{\beta}}_{\text{obs}} = (\boldsymbol{X}'\boldsymbol{X})^{-\mathbf{1}}\boldsymbol{X}'\boldsymbol{y}$ and the component $E(\boldsymbol{U}'\boldsymbol{U})$ propagates as bias.

This shows that adding in additional predictor variables does not guard against bias due to the measurement error in the predictors. The bias is a function of the measurement error in the predictor variables, not a function of the number of variables. However, this illustration does shed light on a possible solution to the problem associated with measurement error in the predictor variables, which we present next.

Accounting for Measurement Error in the Predictor Variables

We first re-express the true score regression as:

$$\mathbf{y}_{\mathrm{t}}^{*} = \mathbf{X}\boldsymbol{\beta} + \sum_{r=1}^{L}\mathbf{y}_{t-r}^{*}\boldsymbol{\gamma}_{t-r} + \sum_{q=1}^{Q}\mathbf{Z}_{q}\boldsymbol{\theta}_{q} + \mathbf{e}$$

We use * to denote the variables without measurement error. For convenience, define the matrices $\mathbf{W} = \{\mathbf{X}, \mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \dots, \mathbf{y}_{t-L}\}$, $\mathbf{W}^{*} = \{\mathbf{X}, \mathbf{y}_{t-1}^{*}, \mathbf{y}_{t-2}^{*}, \dots, \mathbf{y}_{t-L}^{*}\}$, and $\boldsymbol{\delta}' = \{\boldsymbol{\beta}', \boldsymbol{\gamma}'\}$. Label the matrix of measurement error disturbances $\mathbf{U}$ for disturbances associated with $\mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \dots, \mathbf{y}_{t-L}$, and label the vector of measurement disturbances with the dependent variable, $\mathbf{y}_{t}$, $\mathbf{v}$, hence $\mathbf{y}_{t} = \mathbf{y}_{t}^{*} + \mathbf{v}$. Let $\mathbf{U}$ have the same dimension as $\mathbf{W}$, but only the final L columns of $\mathbf{U}$ are non-zero, so $\mathbf{W} = \mathbf{W}^{*} + \mathbf{U}$. If those disturbances were observed, the parameters $\{\boldsymbol{\delta}', \boldsymbol{\theta}'\}$ can be estimated using Henderson's methods (1950) by solving the following mixed model equations:

$$\begin{pmatrix} \boldsymbol{W}^{*\prime}\boldsymbol{\Omega}^{-\mathbf{1}}\mathbf{W}^{*} & \boldsymbol{W}^{*\prime}\boldsymbol{\Omega}^{-\mathbf{1}}\mathbf{Z} \\ \boldsymbol{Z}'\boldsymbol{\Omega}^{-\mathbf{1}}\mathbf{W}^{*} & \boldsymbol{Z}'\boldsymbol{\Omega}^{-\mathbf{1}}\mathbf{Z} + \mathbf{D}^{-\mathbf{1}} \end{pmatrix}\begin{pmatrix} \boldsymbol{\delta} \\ \boldsymbol{\theta} \end{pmatrix} = \begin{pmatrix} \boldsymbol{W}'\boldsymbol{\Omega}^{-\mathbf{1}}\mathbf{y}^{*} \\ \boldsymbol{Z}'\boldsymbol{\Omega}^{-\mathbf{1}}\mathbf{y}^{*} \end{pmatrix}$$

The matrix $\mathbf{D}$ is comprised of Q diagonal blocks, one for each level in the hierarchy. Each diagonal is constructed as $\sigma_{\mathrm{q}}^{2}\mathbf{I}_{q}$ where $\mathbf{I}_{q}$ is an identity matrix with dimension equal to the

number of units at level q, and σ_q^2 is the estimated variance of the random effects among units at level q. When concatenated diagonally the square matrix $\mathbf{D}$ has dimension $m = \sum_{q=1}^{Q} J_q$.

Two complications intervene. First, we cannot observe $\mathbf{U}$, and second, the unobservable nature of this term along with the heterogeneous measurement error in the dependent variable renders this estimator inefficient.

Addressing the first issue, upon expansion we see that

$$\mathbf{W}^{*\prime}\boldsymbol{\Omega}^{-1}\mathbf{W}^{*} = (\mathbf{W}' - \mathbf{U}')\boldsymbol{\Omega}^{-1}(\mathbf{W} - \mathbf{U}) = \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{U} + \mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{U}$$

Since $\mathbf{W} = \mathbf{W}^{*} + \mathbf{U}$, we have $\mathrm{E}(\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{U}) = \mathrm{E}(\mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{U})$, $\mathrm{E}(\mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{W}) = \mathrm{E}(\mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{U})$, hence $\mathbf{W}^{*\prime}\boldsymbol{\Omega}^{-1}\mathbf{W}^{*} = \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{U}$. Furthermore, we have $\mathbf{W}^{*\prime}\boldsymbol{\Omega}^{-1}\mathbf{Z} = \mathrm{E}(\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z})$, $\mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W}^{*} = \mathrm{E}(\mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W})$, and $\begin{pmatrix}\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{y}^{*}\\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y}^{*}\end{pmatrix} = \mathrm{E}\begin{pmatrix}\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{y}\\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y}\end{pmatrix}$.

Addressing the second issue, both the right side and left side variables in the model equation measured with error contribute to the heteroscedasticity. While the correction $\mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{U}$ eliminates the bias due to measurement error, we still do not have an error-free measure of $\mathbf{y}$ for any time period. Therefore, the residual is comprised of

$$\bar{\bar{\mathbf{y}}} - \mathbf{W}'\boldsymbol{\delta} = -\mathbf{U}'\boldsymbol{\delta} + \mathbf{v} + \mathbf{e}.$$

where $\bar{\bar{\mathbf{y}}} = \mathbf{y} - \mathbf{Z}\widetilde{\boldsymbol{\theta}}$, $\widetilde{\boldsymbol{\theta}}$ is the conditional mean of the random effects. The residual variance of any given observation is $\sigma_{ti}^2 = \sigma_e^2 + \sigma_{v(ti)}^2 + \sum_{r=1}^{L} \delta_{t-r}^2 \sigma_{u,t-r(i)}^2$, where $\sigma_{v(ti)}^2$ is known measurement error variance of the dependent variable for examinee *i* at time *t*. Similarly, $\sigma_{u,t-r(i)}^2$ are the known measurement error variances of *r* prior test scores. Now, let $\boldsymbol{\Omega}$ be a diagonal matrix of dimension *N* with diagonal elements σ_{ti}^2.

With the above, we can define the mixed model equations as

$$\begin{pmatrix}\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{U} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z}\\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} + \mathbf{D}^{-1}\end{pmatrix}\begin{pmatrix}\boldsymbol{\delta}\\ \boldsymbol{\theta}\end{pmatrix} = \begin{pmatrix}\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{y}\\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y}\end{pmatrix}$$

Replacing $U'\Omega^{-1}U$ with Its Expectations

As indicated, $\mathbf{U}$ is unobserved and so solving the mixed model equation cannot be computed unless $\mathbf{U}$ is replaced with some observed values. First, we redefine the mixed model equations as:

$$\begin{pmatrix}\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z}\\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} + \mathbf{D}^{-1}\end{pmatrix}\begin{pmatrix}\boldsymbol{\delta}\\ \boldsymbol{\theta}\end{pmatrix} = \begin{pmatrix}\mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{y}\\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y}\end{pmatrix}$$

where $\mathbf{S}$ is a diagonal "correction" matrix with dimensions *p* x *p* accounting for measurement error in the predictor variables, $p = p_{\mathbf{X}} + L$, and $p_{\mathbf{X}}$ is the column dimension of $\mathbf{X}$.

The matrix $\mathbf{S}$ is used in lieu of $\mathbf{U}'\boldsymbol{\Omega}^{-1}\mathbf{U}$ based on the following justification. Recall that we previously defined $\boldsymbol{\Omega}$ as $\mathrm{diag}(\sigma_{t1}^2, \sigma_{t2}^2, \dots, \sigma_{tN}^2)$ and the matrix of unobserved disturbances is:

$$\boldsymbol{U} = \begin{bmatrix} \mathbf{0}_{p_{\mathrm{X}}} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{U}_L \end{bmatrix}$$

where $\mathbf{0}_{p_{\mathbf{X}}}$ is a matrix of dimension of $p_{\mathbf{X}}$ with elements of 0, and

$$\boldsymbol{U}_L = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1L} \\ u_{21} & u_{22} & \dots & u_{2L} \\ \vdots & \vdots & \ddots & \vdots \\ u_{N1} & u_{N2} & \dots & u_{NL} \end{bmatrix}$$

The theoretical result of the matrix operation yields the following symmetric matrix:

$$\mathbf{U}_{\mathrm{L}}{}'\boldsymbol{\Omega}^{-1}\mathbf{U}_{\mathrm{L}} = \begin{bmatrix} \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} u_{i1}^2 & & \dots & \\ \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} u_{i1} u_{i2} & \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} u_{i2}^2 & \dots & \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} u_{i1} u_{iL} & \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} u_{i2} u_{iL} & \dots & \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} u_{iL}^2 \end{bmatrix}$$

The theoretical result is limited only because we do not observe u_{ip}--it is latent. However, $E(u_{ip}u_{ip}) = \sigma_{ip}^2$ where σ_{ip}^2 is taken as the conditional standard error of measurement for student *i*. The theoretical result also simplifies because errors of measurement on different variables are by expectation uncorrelated, $E(u_{ip}u_{ip'}) = 0$ where $p \neq p'$.

Because we now have a conditional standard error of measurement that varies for each student *i* and we can ignore the off-diagonals, let **S** be:

$$\mathbf{S} = \mathrm{diag}\left(0, \dots, 0, \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} \sigma_{u,t-1(i)}^2, \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} \sigma_{u,t-2(i)}^2, \dots, \sum_{i=1}^{N} \frac{1}{\sigma_{ti}^2} \sigma_{u,t-L(i)}^2\right)$$

where $\sigma_{u,j(i)}^2$ denotes the measurement error variance for the *j*th, *j* = (1, 2, … *L*), variable measured with error.

Empirical Bayes versus Fixed Effects

We previously noted that the general model can estimate teacher impacts as fixed or random effects. We also note that the Florida value added teacher effects are empirical Bayes estimates and explicitly defined the teacher effects as such. These types of models are also referred to as "shrinkage" estimators as some of the teacher and school effects are pulled towards a conditional mean given their level of reliability.

The "shrinkage" in the empirical Bayes estimates introduces a small amount of bias, but yields a smaller mean squared error. Conversely, fixed effects models produce unbiased estimates, but

have larger mean squared error. As a result of this bias-variance trade-off, the empirical Bayes are, on average, closer to the true population parameter than the fixed effect estimator.

We previously discussed with the Student Growth Implementation Committee that fixed and random effects measure the same quantity and would expect them to be highly correlated. Here we make that argument explicit and show how the fixed effects estimator is the same as the random effects estimator with a small constraint.

Recall that the mixed model solution is based on Henderson's equations:

$$\begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} + \mathbf{D}^{-1} \end{pmatrix} \begin{pmatrix} \boldsymbol{\delta} \\ \boldsymbol{\theta} \end{pmatrix} = \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{y} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y} \end{pmatrix}$$

The system simultaneously solves for $\boldsymbol{\delta}$ and $\boldsymbol{\theta}$. However, for illustration suppose we are interested only in solving for the random effects, $\boldsymbol{\theta}$:

$$(\mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} + \mathbf{D}^{-1})\boldsymbol{\theta} = \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y} - \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W}\boldsymbol{\delta}$$

Now suppose that we estimate teachers as fixed effects. The linear model would be:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

where **y** is an *n* x 1 vector of outcomes, **X** is an *n* x *q* design matrix $\boldsymbol{\beta}$ is a *q* x 1 vector of coefficients and **e** is a random error term, $\boldsymbol{e} \sim N(0, \sigma_e^2)$. Because there are many teachers, suppose we partition **X** as **X** = [**W Z**], where **W** corresponds to non-teacher related fixed effects, and **Z** corresponds to teacher level fixed effects, similarly, we partition $\boldsymbol{\beta}$ as $\boldsymbol{\beta} = [\boldsymbol{\delta}' \quad \boldsymbol{\theta}']$ thus yielding:

$$\mathbf{Y} = \mathbf{W}\boldsymbol{\delta} + \mathbf{Z}\boldsymbol{\theta} + \mathbf{e}$$

The normal equation for a partitioned regression is (Searle, 1997):

$$\begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \end{pmatrix} \begin{pmatrix} \boldsymbol{\delta} \\ \boldsymbol{\theta} \end{pmatrix} = \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{y} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y} \end{pmatrix}$$

And isolating the solution for the teacher fixed effects yields:

$$\mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}\boldsymbol{\theta} = \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{y} - \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W}\boldsymbol{\delta}$$

Hence, we can see that the random effects estimator is the same as the fixed effects estimator when all elements in the matrix **D** are null. In fact, the matrix **D** is what controls the amount of shrinkage observed in the data.

Standard Errors of Fixed and Random Effects

Henderson's method provides that the standard errors of the fixed and random effects can be computed as:

$$\mathrm{Var}\begin{pmatrix} \boldsymbol{\delta} \\ \boldsymbol{\theta} \end{pmatrix} = \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{S} & \mathbf{W}'\,\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\,\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} + \mathbf{D}^{-1} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{W}'\,\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\,\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} + \mathbf{D}^{-1} \end{pmatrix} \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} - \mathbf{S} & \mathbf{W}'\,\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\,\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z} + \mathbf{D}^{-1} \end{pmatrix}^{-1}$$

Note that

$$\begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix} \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1}$$

$$= \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1} \left[\begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix} + \begin{pmatrix} \mathbf{S} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \right] \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1}$$

$$= \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1} + \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{S} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1}$$

Let $\begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix} = \begin{pmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}' & \mathbf{C} \end{pmatrix}$ and $\begin{pmatrix} \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{W}-\mathbf{S} & \mathbf{W}'\boldsymbol{\Omega}^{-1}\mathbf{Z} \\ \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{W} & \mathbf{Z}'\boldsymbol{\Omega}^{-1}\mathbf{Z}+\mathbf{D}^{-1} \end{pmatrix}^{-1} = \begin{pmatrix} \mathbf{C}_{11} & \mathbf{C}_{12} \\ \mathbf{C}'_{12} & \mathbf{C}_{22} \end{pmatrix}$. Then we have $\mathbf{C}_{11} = (\mathbf{A}-\mathbf{B}\mathbf{C}^{-1}\mathbf{B}')^{-1}$, $\mathbf{C}_{12} = -(\mathbf{A}-\mathbf{B}\mathbf{C}^{-1}\mathbf{B}')^{-1}\mathbf{B}\mathbf{C}^{-1}$ and

$$\mathbf{C}_{22} = \mathbf{C}^{-1} + \mathbf{C}^{-1}\mathbf{B}'(\mathbf{A}-\mathbf{B}\mathbf{C}^{-1}\mathbf{B}')^{-1}\mathbf{B}\mathbf{C}^{-1}.$$

Note that if we assume that no teachers teach at more than one school (and we order the columns in $\mathbf{Z}$ appropriately) and no student was associated with more than one school, the $\mathbf{C}$ matrix is block diagonal with a block for each school containing entries for each of the teachers teaching at that school. Under this assumption $\mathbf{C}^{-1}$can be computed efficiently and the other computations also become tractable even for very large datasets. If there are some students who were in two or more schools during the current year, we will have a few entries in the matrix that are not on the block diagonal, but these will simply be ignored for the purposes of computing the variance terms.

We now have

$$var\begin{pmatrix} \boldsymbol{\delta} \\ \boldsymbol{\theta} \end{pmatrix} = \begin{pmatrix} \mathbf{C}_{11} & \mathbf{C}_{12} \\ \mathbf{C}'_{12} & \mathbf{C}_{22} \end{pmatrix} + \begin{pmatrix} \mathbf{C}_{11}\mathbf{S}\mathbf{C}_{11} & \mathbf{C}_{11}\mathbf{S}\mathbf{C}_{12} \\ \mathbf{C}'_{12}\mathbf{S}\mathbf{C}_{11} & \mathbf{C}'_{12}\mathbf{S}\mathbf{C}_{12} \end{pmatrix}$$

The standard errors of the fixed effects are computed as:

$$var(\boldsymbol{\delta}) = \mathbf{C}_{11} + \mathbf{C}_{11}\mathbf{S}\mathbf{C}_{11}$$

And the conditional variances of the random effects are:

$$\mathrm{E}\left(\mathrm{Var}(\widetilde{\boldsymbol{\theta}}|\mathbf{y})\right) = \mathrm{E}[\mathbf{C}_{22} + \mathbf{C}'_{12}\mathbf{S}\mathbf{C}_{12}]$$

In order to compute the variances we only care about the diagonal and $\mathbf{C}'_{12}\mathbf{S}\mathbf{C}_{12}$ can be computed easily if $\mathbf{C}$ is block diagonal. That is, the ith diagonal block comes from the ith diagonal block $\mathbf{C}_{\mathrm{i}}$ of $\mathbf{C}$, and the ith block $\mathbf{B}_i$ of $\mathbf{B}$. It equals: $\mathbf{C}_i^{-1}\mathbf{B}'_i(\mathbf{A}-\mathbf{B}\mathbf{C}^{-1}\mathbf{B}')^{-1}\mathbf{S}(\mathbf{A}-\mathbf{B}\mathbf{C}^{-1}\mathbf{B}')^{-1}\mathbf{B}_i\mathbf{C}_i^{-1}$.

Hence, at level q, the conditional variances are:

$$\mathrm{E}\left(\mathrm{Var}(\widetilde{\boldsymbol{\theta}}_q|\mathbf{y})\right) = \frac{1}{J_q}\mathrm{tr}\left(\mathrm{Var}(\widetilde{\boldsymbol{\theta}}|\mathbf{y})_q\right)$$

where tr(.) denotes the trace of the matrix, and $var(\widetilde{\boldsymbol{\theta}}|\mathbf{y})_q$ is the submatrix containing the entries at level q. We can now compute σ_q^2 as

$$\sigma_q^2 = \mathrm{E}\left(\mathrm{var}(\widetilde{\boldsymbol{\theta}}_q|\mathbf{y})\right) + \frac{1}{q-1}\left(\boldsymbol{\theta}_q - m_{\boldsymbol{\theta}_q}\mathbf{1}\right)'\left(\boldsymbol{\theta}_q - m_{\boldsymbol{\theta}_q}\mathbf{1}\right)$$

where $m_{\boldsymbol{\theta}_q}$ is the mean of $\boldsymbol{\theta}_q$ and $\mathbf{1}$ is a vector of 1's with the same dimension as $\boldsymbol{\theta}_q$.

The residual variance can now be estimated as

$$\sigma_e^2 = \mathrm{Var}(\mathbf{e}) - \frac{1}{N}\left(\sum_{i=1}^{N}\left(\sigma_{v(ti)}^2 + \sum_{r=1}^{L}\delta_{t-r}^2\sigma_{u,t-r(i)}^2\right)\right)$$

where $\mathbf{e} = \bar{\bar{\mathbf{y}}} - \mathbf{W}\boldsymbol{\delta}$ and $var(\mathbf{e}) = \frac{\mathbf{e}'\mathbf{e}}{N-p}$, N is the total number of students and p is the number of fixed effect parameter estimated.

Computing the Value-Added Model

Our implementation of the value added model uses the well-known Expectation-Maximization (EM) algorithm (Dempster, Laird, Rubin; 1977) to solve the mixed model equations. All computing takes place within SAS IML, which has functions for sparse matrix methods, including a sparse Cholesky decomposition. These methods make computing more feasible to larger data sets when the matrices retain their sparseness.

The solutions for the fixed effects and predictions for the random effects are obtained via the Expectation-Maximization (EM) algorithm via the following steps:

1. Construct starting values for the variances of the random effects including σ_e^2 and σ_q^2 for all levels of q. These are used in the matrices $\boldsymbol{\Omega}$ and $\mathbf{D}$, respectively.

2. Solve the linear system for $\boldsymbol{\delta}$ and $\boldsymbol{\theta}$. The system is sparse and can be solved using sparse matrix methods.

3. Update the values of the variances of the random effects including σ_e^2 and σ_q^2 using the methods described above.

4. Iterate between steps 2 and 3 until $\left|\boldsymbol{\delta}_j^t - \boldsymbol{\delta}_j^{t-1}\right| < \mathrm{con}\ \forall\ j$ where con is the convergence criteria by default set at 1e-5.

If teacher and school effects are treated as fixed rather than random, the estimation method above is used with the constraint that all elements of the matrix $\mathbf{D}$ are 0 and the only variance parameter updated at each iteration is σ_e^2 as justified in the previous section on fixed effects estimation.

Final Estimates of the Teacher Value-Added Score

We previously noted that the SGIC wanted some of the unique school component to be added back to the teacher effect. We formally denote the teacher value-added score then as:

$$\theta_t^* = \theta_t + .5\theta_{(s)t}$$

Where θ_t is the empirical Bayes estimate of the teacher effect, $\theta_{(s)t}$ is the empirical Bayes estimate of the unique school component and the notation *s(t)* is used to mean that teacher *t* is in school *s*. Because the revised teacher effect is a linear combination of the teacher and school effects, the final conditional variance of the teacher effect no longer applies and we require a new variance estimator. However, this is easily established using the conditional variances of the empirical Bayes estimates as the variance of the linear combination, which we denote as:

$$var(\theta_t^*) = var(\theta_t) + .25var\left(\theta_{(s)t}\right) + \ cov(\theta_t, \theta_{(s)t})$$

Classification Probabilities

The standard errors of the teacher effects represent the measurement of uncertainty associated with a given effect. However, we can extend this to compute other measures that indicate the degree to which teachers could be inaccurately classified as having high or low value added measures.

Suppose we begin with a true score measurement model for teacher effects such that the observed teacher effect is the sum of a true effect and measurement error:

$$\theta = \theta^* + e$$

In value-added models, the goal is to identify teachers[§] whose *effects* are sufficiently large to judge them as being "high performing." Hence, a teacher is deemed high performing within a VAM context when $\theta > t$; or their observed effect is larger than a pre-determined threshold, *t*.

Value-added modeling researchers often estimate θ in different ways and they often vary in how they define *t*. However, this section establishes a general framework for VAM classification accuracy for models that establish teacher effects using a classical measurement framework. Model-specific classification probabilities can be subsequently derived based on the following theory.

Given this structural model for teacher effects and assuming normality of the error distribution, the marginal probability of a teacher being identified as effective can be derived as:

$$\begin{aligned} \Pr(\theta > t) &= \Pr(\theta^* + e > t) \\ &= \Pr(e > t - \theta^*) \\ &= \Pr(e < \theta^* - t); f(e) \sim N(0, \sigma_e^2) \\ &= \Phi\left(\frac{\theta^* - t}{\sigma_e}\right) \end{aligned}$$

where $\Phi(.)$ denotes the normal cumulative distribution function. Managing risk requires an examination of the false positives, or the identification of teachers classified as effective when they truly are not. Extending this to examine false positive rates requires the joint probability:

$$\Pr(\theta > t, \theta^* < t) = \Pr(\theta^* < t | \theta > t) \Pr(\theta > t)$$

[§] This framework generalizes beyond teachers and can yield classification probabilities for any aggregate unit

$$= \int_{-\infty}^{t} \Phi\left(\frac{\theta^* - t}{\sigma_e}\right) f\left(\theta^* \middle| \mu_{\theta^*}, \sigma_\theta^2\right) d\theta^*$$

This yields, for each teacher, a misclassification probability. Introducing the subscript *j* to denote individual teachers (for *i = 1, …, N*), we can now establish:

$$\mathrm{E(FP)} = \sum_{j=1}^{N} \Pr(\theta_j > t, \theta_j^* < t)$$

where E(FP) denotes the expected number of false positives given the data. Supposing we observe Q teachers falling above the threshold *t*, we can compare E(FP) to Q where it is expected that $\mathrm{E(FP)} < Q$.

Additionally, we can use the same assumptions made previously and justify the following in order to compute the false negatives

$$\Pr(\theta < t, \theta^* > t) = \int_{t}^{\infty} \Phi\left(\frac{t - \theta^*}{\sigma_e}\right) f\left(\theta^* \middle| \mu_{\theta^*}, \sigma_\theta^2\right) d\theta^*$$

$$\mathrm{E(FN)} = \sum_{j=1}^{N} \Pr(\theta_j < t, \theta_j^* > t)$$

Simulations

To ensure the accuracy of the measurement-error corrected mixed model equations, AIR conducted a series of simulations. We constructed test data sets that varied along five dimensions. While the focus of the estimates is on teacher effects, the model should handle multiple levels in the educational hierarchy. We vary the simulated data according to the following:

- Magnitude of effect at each level.
- Measurement properties of the test. IRT tests have measurement variances that vary across the range of scale scores. Classical test theory (and existing programs based on it) assume a constant measurement variance across the range.
- Number of lags. The model controls for prior achievement. Simulations should include immediately prior and previous lagged achievement scores.
- Variation in school and class size.
- Selection model. We know that students are not sorted into classrooms randomly. This varies the extent to which students are sorted into classrooms based on observed scores.

Configurations

The chart below summarizes the parameter settings for four simulation configurations. Each run included approximately 200 top-level units (i.e., schools or districts), and were run on 800 independently generated data sets.

Exhibit 1. Data configurations

Simulation model	Meas. Properties	Magnitude of effect at each level	Levels	Size Variation	Selection effect	Covariates	Time Lags
Simple/baseline	Constant	Moderate (.2)	2	Low (m=20,v=16)	None	None	1 (prior effect=.8)
Basic	Asymmetric	Moderate (.2)	3	Moderate (school: m=20, v=100; teacher m=20, v=80)	Some (.0225 at each level)	Some (2, both N(0,1); coef = .1,-.1)	1 (prior effect=.8)
Two Lags	Asymmetric	Moderate (.2)	3	Moderate (school: m=20, v=100; teacher m=20, v=80)	Some (.0225 at each level)	(2, both N(0,1); coef = .1,-.1	2 (prior effect=.8)
Small effects	Asymmetric	Small (.05)	3	Moderate (school: m=20, v=100; teacher m=20, v=80)	Some	Some	1

Quality of model parameters

Statistical indicators of model quality included indicators of:

- Bias
- Precision
- Quality of standard errors
- Bias of estimated teacher effects
- Quality of standard errors of estimated teacher effects

Exhibit 2 describes the indicators of bias and precision for the parameters of the model. Each simulation should recover unbiased estimates of the parameters.

Exhibit 2. Indicators of bias and precision

Indicator of:	Indicator for each model parameter
Observed bias	Average estimate – true value
Sampling error	Average standard deviation of estimates across replicates
Combined sampling error and bias	Root mean square error across replicates $(estimate - true\,value)^2$

Exhibit 3 summarizes the indicators of the quality of the standard errors.

Exhibit 3. Indicators of unbiasedness and consistency of the standard error estimators

Indicator of:	Indicator for each model parameter
Observed standard error	Standard deviation across replicates
Estimated standard error	Average estimated standard error across replicates
Unbiasedness	Average of $ratio = \dfrac{Average\,SE\,estimate}{root\,MSE}$ across items
Unbiasedness	Proportion of 200 datasets where $p(t)\left(\dfrac{estimate - true\,value}{\text{estimated SE}}\right) < .05$
Unbiasedness	Proportion of 200 datasets where $p(t)\left(\dfrac{estimate - true\,value}{\text{estimated SE}}\right) < .10$

Quality of unit (teacher or school) effects

Exhibit 4. Indicators of bias and precision

Indicator of:	Indicator for each model parameter
Observed bias	Average across replicates, average across teachers and schools: estimate – true value
Sampling error	Calculate the mean, standard deviation, min and max of the standard error estimate for each replicate. Report the average of these statistics and put the 200 estimates in an appendix.
Combined sampling error and bias	Root mean square error across replicates $(estimate - true\,value)^2$

Exhibit 5 summarizes the indicators of the quality of the standard errors.

Exhibit 5. Indicators of unbiasedness and consistency of the standard error estimators

Indicator of:	Indicator for each model parameter
Unbiasedness	Proportion of estimates across all 200 datasets (200*N teachers) where $p(t)\left(\frac{estimate - true\,value}{\text{estimated SE}}\right) < .05$
Unbiasedness	Proportion of estimates across all 200 datasets where $p(t)\left(\frac{estimate - true\,value}{\text{estimated SE}}\right) < .10$

To evaluate the quality of the school and teacher effect estimates, we propose to calculate the estimated effects and compare them to the true effects using statistics similar to those described in Exhibits 2 and 3.

RESULTS

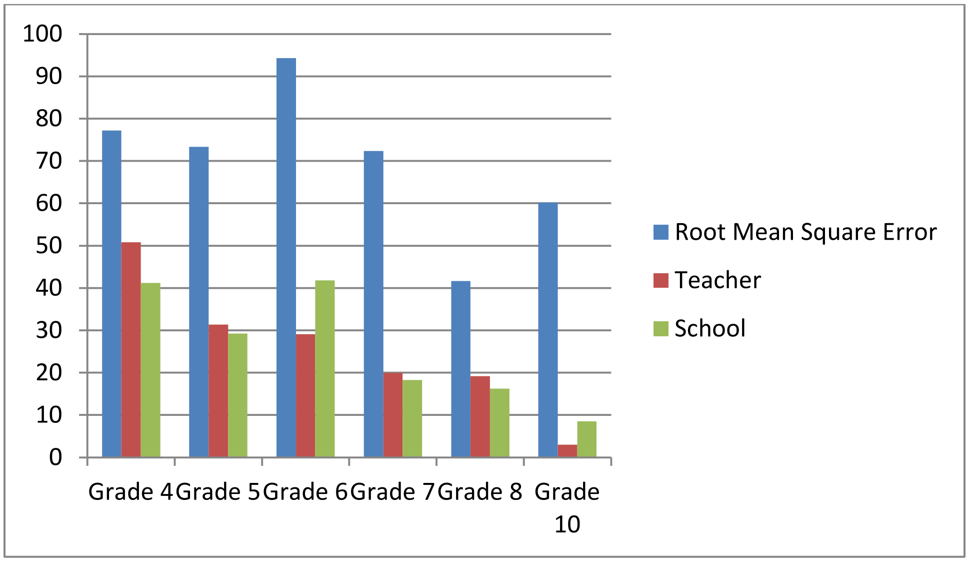
In this section we provide summaries of the model results for reading and math across all grades for the 2010-11. [**]The appendices provide tables showing results in further detail.

Teacher and School Variance Components

For each grade, the value-added models were fit to the data with both teacher and school random effects. The model decomposes total variation in the outcome into three orthogonal components: variance between teachers within a school, variance between schools, and variance between students within a class. Figures 2 and 3 below show the standard deviation of the student, teacher, and school components in reading and math across all grades.

[**] The 2010-11 model does not include the attendance or mobility covariates because the data was not available from the FLDOE at the time of the analysis; these covariates will be included and results provided to the state in late fall 2011.

Figure 2. Magnitude of Teacher and School Variance Components: Mathematics



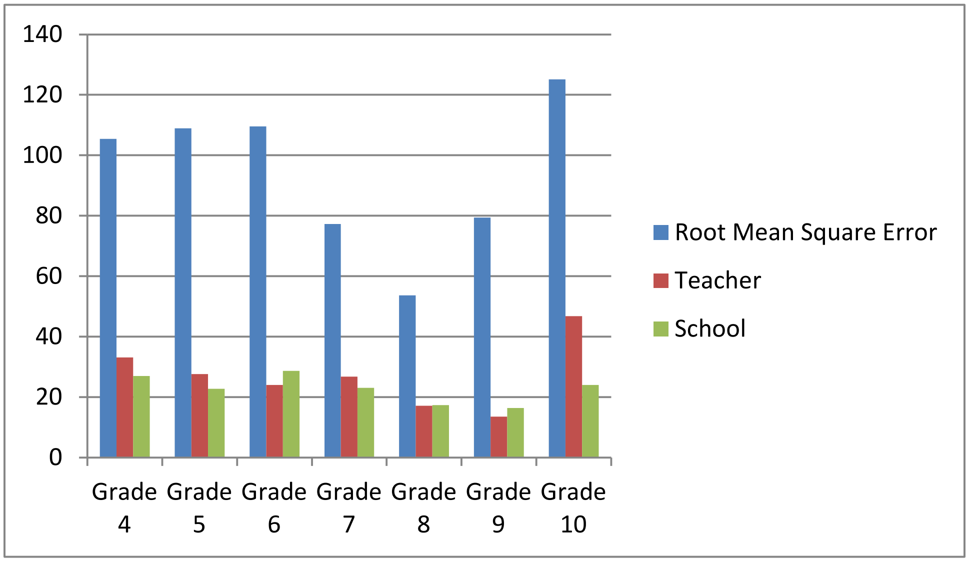
Formal likelihood ratio tests are not performed between models with teacher effects only and those with both teacher effect and school component. However, using the visual displays as a heuristic to gauge the magnitude of the variance components, we observe that school components seem to account for a non-trivial amount of the variance in the outcome variable.

The relatively sizable magnitude of the school components suggest that systematic school components exist and explain differences in how students perform, above and beyond that which is explained by the teacher effects. In general, the variance between schools tends to be smaller than the variance between teachers within a school. The notable exception to this trend is grade 6 math, where the two effects appear to have similar magnitudes.

It is clear that the variance between students within a class is the largest of all variance components. In reading, there remains quite a bit of heterogeneity between students within a class across all grades. However, the math plots suggest greater homogeneity in students within a class as we look at the higher grades.

It is also worth noting that in math there is an apparent, systematic decline in the variance between schools and the variance between teachers within a school as we look in the higher grades.

Figure 3. Magnitude of Teacher and School Variance Components: Reading



Teacher and School Standard Errors

When value-added models estimate teacher effects and school components, they do so with a certain level of uncertainty. Factors such as the variation in student scores, the type and number of students attributed to a school, and the number of teachers in a school can all influence this level of uncertainty. The level of uncertainty for a particular teacher effect or school component is summarized in the standard error for each estimate.

Table 1 shows the mean of the conditional standard errors of the teacher and school empirical Bayes estimates disaggregated by grade and subject. Within each grade and subject, it can be seen that on average, school components are more precise than the corresponding teacher effects – as would be expected given that more students are typically attributed to a school than to an individual teacher.

While the relationship between teacher and school precision seems to be consistent across grades, the standard errors vary considerably across grades. This variability indicates that the model for some grades is producing teacher effects and school components with less uncertainty than other grades. The standard errors of teacher effects for reading range from a minimum of 8.98 for grade 5, to a maximum of 16.37 for grade 10. For mathematics, grade 9 has the most precise teacher effects on average (7.9), whereas grade 5 has the least precise teacher effects (24.37).

Table 1. Mean Teacher and School Standard Errors by Grade and Subject

	Reading		Mathematics	
Grade	**Teacher**	**School**	**Teacher**	**School**
5	8.98 (0.58)	6.85 (1.12)	24.37 (4.44)	15.1 (2.42)
6	14.9 (1.82)	8.05 (1.57)	18.85 (3.86)	13.91 (3.69)
7	15.77 (1.98)	7.77 (1.33)	14.88 (4.28)	8.71 (1.50)
8	12.84 (1.74)	6.35 (1.07)	9.45 (2.22)	5.7 (0.99)
9	9.82 (0.89)	5.23 (1.14)	7.9 (2.03)	4.25 (1.00)
10	16.37 (1.85)	6.86 (1.57)	6.46 (0.84)	3.51 (0.92)

Impact of VAM on Different Student Groups

It is important to examine the possible disparate impact that the VAM has on different groups of students. A difference in expectations does not necessarily imply issues inherent in the model. Some of the observed differences are plausible. In this section we provide descriptive statistics showing how the growth-based model predictions may vary across different student groups.

Below we use the term expected growth, a statistic which we compute as:

$$g_i = \hat{y}_{it} - y_{i,t-1}$$

Where $\hat{y}_{it}$ is the predicted outcome and $y_{i,t-1}$is the observed outcome. This expected growth is aggregated at various levels to examine possible differences in mean growth expectations.

Differences in Student Growth Expectations by Gifted Status

To examine whether student growth expectations differ for gifted and non-gifted students, conditional expected growth estimates were calculated separately for gifted and non-gifted students at each grade level for both mathematics and reading. Figures 4 and 5 below display these expected growth estimates by grade for mathematics and reading, respectively.

Figure 4. Expected Growth for Gifted and Non-Gifted Status Students by Grade: Mathematics

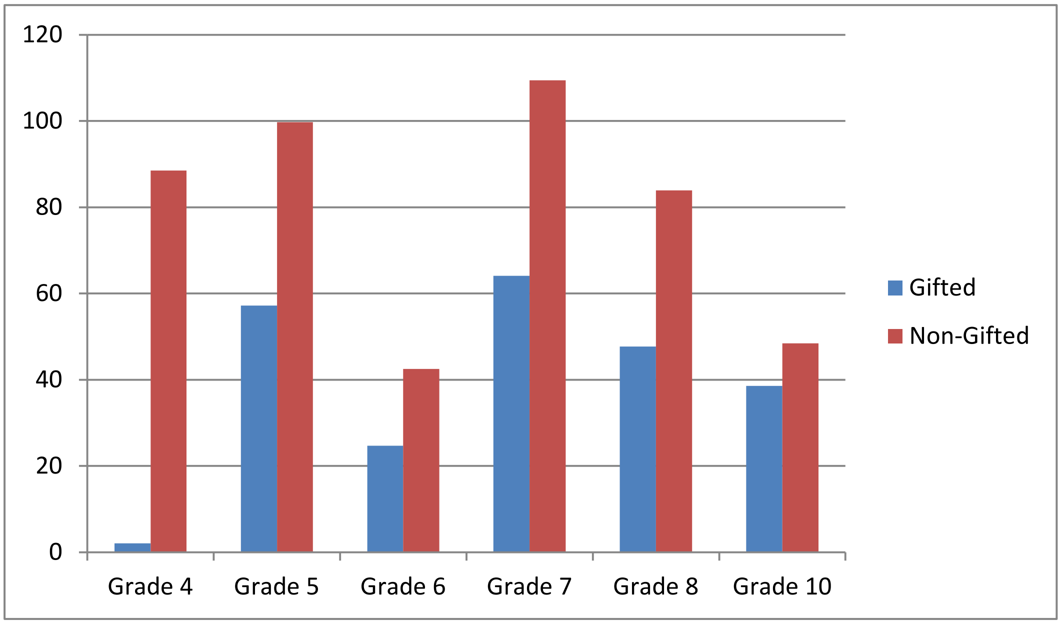


Figure 5. Expected Growth for Gifted and Non-Gifted Status Students by Grade: Reading

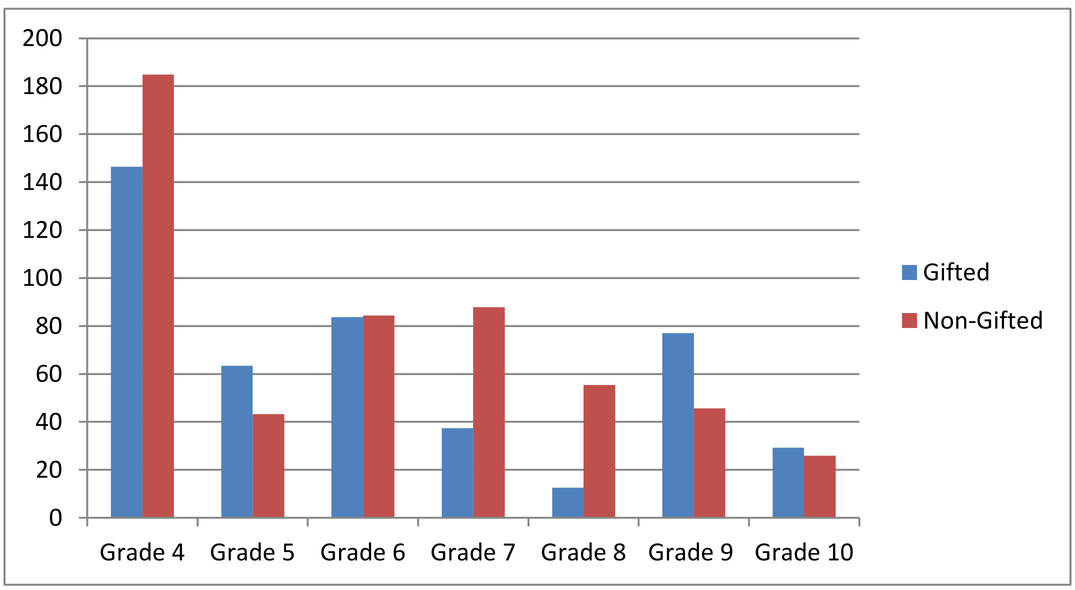


Figure 4 demonstrates that student growth expectations in mathematics were higher for non-gifted than for gifted students in all grades tested. For reading, Figure 5 demonstrates that student growth expectations were higher for gifted than for non-gifted students in grades 5, 9 and 10, approximately equivalent for grade 6 and lower for gifted than for non-gifted students in grades 4, 7 and 8.

It is important to interpret any observed differences between students with gifted and non-gifted status with caution given considerable differences in the size of the population of students for

which these estimates were calculated. For example, for grade 10 reading, the expected growth for gifted students is based on 194 students in contrast to 175,184 non-gifted students. A comprehensive display of the student growth estimates and associated sizes of the student populations used to calculate each estimate is provided in Appendix F. Together, these findings demonstrate higher growth expectations for non-gifted than gifted students in mathematics but no consistent relationship between gifted status and conditional expectations for student growth in reading.

Differences in Conditional Student Growth Expectations by ELL Status

Similarly, it is possible that English Language Learners (ELLs) differ from their non-ELL counterparts in expectations for student growth. To examine this possibility, conditional expected growth estimates were calculated separately for ELL and non-ELL students at each grade level for both mathematics and reading. Figures 6 and 7 below display these expected growth estimates by grade for mathematics and reading, respectively.

Figure 6. Expected Growth for ELL and Non-ELL Status Students by Grade: Mathematics

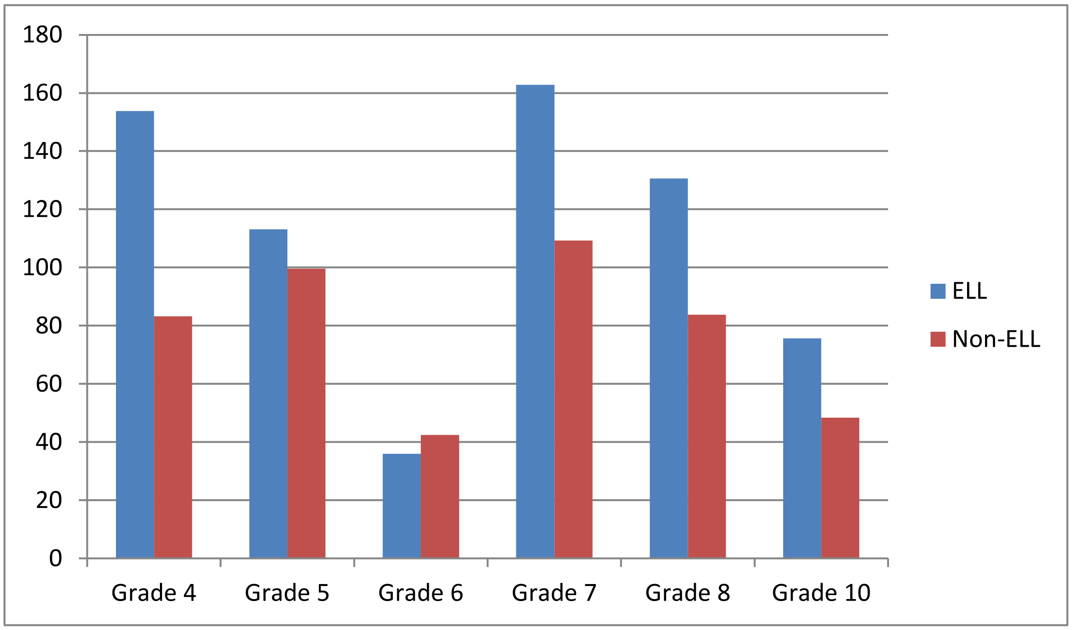


Figure 7. Expected Growth for ELL and Non-ELL Status Students by Grade: Reading

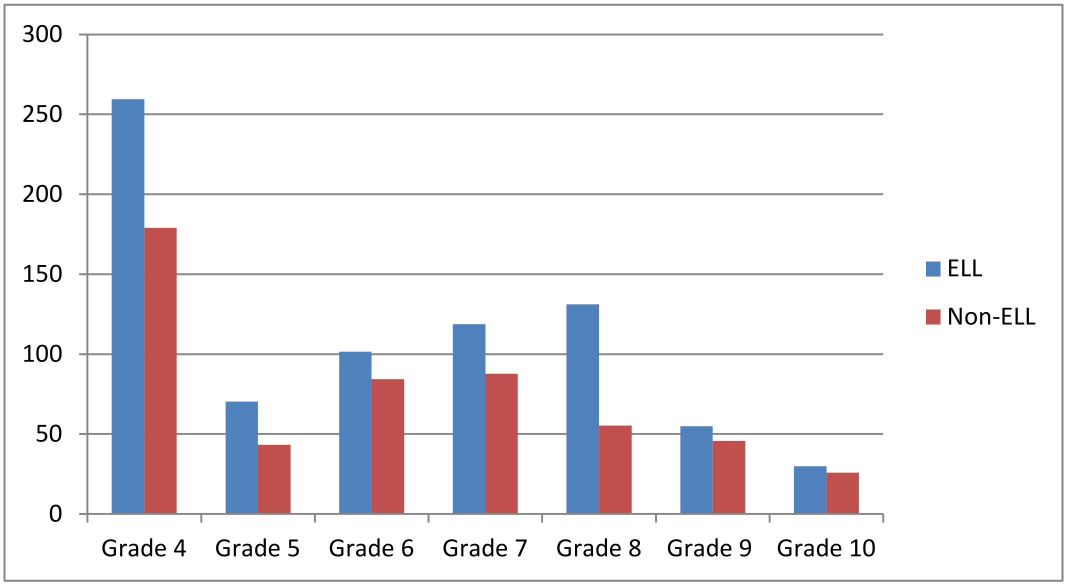


Figure 6 demonstrates that student growth expectations in mathematics were higher for ELL than for non-ELL students in all grades except grade 6. For reading, Figure 7 demonstrates that student growth expectations were higher for ELL than non-ELL students in grades 4 through 10.

Again, it is important to interpret any observed differences between ELL and non-ELL students given considerable differences in the size of the population of students for which these estimates were calculated. For example, for grade 10 mathematics, the expected growth for ELL students is based on 123 students relative to 156,089 non-ELL students. A comprehensive display of the student growth estimates and associated sizes of the student populations used to calculate each estimate is provided in Appendix F. Together, these findings demonstrate higher conditional growth expectations in mathematics and reading for ELL than non-ELL students with one exception (grade 6 mathematics).

Effects of Teacher Characteristics on Teacher Value-Added Estimates

We can also examine whether value-added estimates for teachers are related to teacher characteristics such as teaching experience (years teaching) and teacher education (highest degree earned) as well as the characteristics of teachers' classrooms such as the percentage of students who are ELLs and/or who have disabilities. To examine these possibilities, we calculated the correlations between teacher value-added estimates and the teacher (experience) and classroom characteristics (percent ELL, percent of students with disabilities). Additionally, we present the average teacher value-added estimate separately for teachers with different levels of higher education.

Here we show the correlations across all grades (4-10, excluding grade 9 for mathematics; 4-10 for reading). Appendix G provides these same results separately by grade.

Table 2 displays the correlations between teacher effects for mathematics and reading (separately) and teaching experience, the percentage of ELL students and the percentage of

students with disabilities within teachers' classrooms. Table 3 displays the average teacher value-added estimates for mathematics and reading for teachers with bachelors, masters, and doctorate degrees.

Table 2. Relationship between Teacher Effects for Mathematics and Reading and Teacher and Classroom Characteristics

Teacher/Classroom Characteristic	Mathematics R	Mathematics N	Reading R	Reading N
Teacher Experience (Years Teaching)	0.026	44,401	0.045	59,247
Percent ELLs	0.011	45,886	0.008a	61,409
Percents Students with a Disability	-0.055	45,886	-0.022	61,409

Note: a Correlation not statistically significant at the 0.05 level.

Table 2 shows the observed correlations with the teacher characteristics. These correlations are all very small in magnitude, but are worth examining. For both mathematics and reading, teacher value-added estimates are positively correlated with the percentage of ELLs in teachers' classrooms and teaching experience, and negatively correlated with the percentage of students with a disability in teachers' classrooms. Teachers who have been teaching longer, who have a greater proportion of ELL students in their classroom, and a smaller proportion of students with a disability have larger effects.

Table 3. Average Teacher Value-Added Estimates for Mathematics and Reading by Teacher Education

Teacher Education (Highest Degree)	Mathematics Mean	Mathematics SD	Mathematics N	Reading Mean	Reading SD	Reading N
Bachelor's Degree	0.21	30.79	28,804	-0.09	18.95	36,726
Master's Degree	1.46	30.34	14,494	1.23	19.12	20,830
Doctorate Degree	-1.26	27.69	383	0.60	18.75	612

Table 3 provides the mean value-added estimate in reading and math conditional on teachers' highest degree. In mathematics, teacher value-added estimates were larger for teachers who had completed a master's degree followed by teachers with a bachelor's degree and a doctorate degree. For reading, teachers with a master's degree showed the largest teacher value-added estimates on average, followed by teachers with a doctorate degree and teachers with a bachelor's degree. Thus, there is not a direct relationship between teacher education and teacher value-added estimates; teachers with master's degree demonstrate the highest value-added estimates in both mathematics and reading.

Simulation Results

Quality of Unit (Teacher or School) Effects

The tables below provide summaries of the statistics outlined in the Methods section. In almost all cases, our EiV mixed model recovers the parameter estimates for both the fixed and random effects. In a few cases, there is a very small bias in the fixed effects parameters as observed in Table 4. We note that correction for measurement error reduces, but does not totally eliminate, bias in the parameters. All variants of the model produce unbiased estimates of teacher and school effects.

Table 4. Unbiasedness of the Fixed Effects Parameters

	Simple/Baseline	Basic	Two Lags	Small Effects
Observed Bias Parameter 1	0.013	0.000	0.000	0.000
Observed Bias Parameter 2		0.000	0.000	0.000
Observed Bias Parameter 3		0.013	0.012	0.011
Observed Bias Parameter 4			0.003	
Sampling Error Parameter 1	0.009	0.003	0.004	0.003
Sampling Error Parameter 2		0.003	0.005	0.003
Sampling Error Parameter 3		0.005	0.011	0.006
Sampling Error Parameter 4			0.010	
Combined Sampling Error and Bias Parameter 1	0.016	0.003	0.004	0.003
Combined Sampling Error and Bias Parameter 2		0.003	0.005	0.003
Combined Sampling Error and Bias Parameter 3		0.014	0.016	0.012
Combined Sampling Error and Bias Parameter 4			0.010	

Table 5. Standard Errors of the Fixed Effects Parameters

	Simple/Baseline	Basic	Two Lags	Small Effects
Observed Standard Error Parameter 1	0.009	0.003	0.004	0.003
Observed Standard Error Parameter 2		0.003	0.005	0.003
Observed Standard Error Parameter 3		0.005	0.011	0.006
Observed Standard Error Parameter 4			0.010	
Estimated Standard Error Parameter 1	0.008	0.003	0.004	0.003
Estimated Standard Error Parameter 2		0.003	0.004	0.003
Estimated Standard Error Parameter 3		0.005	0.011	0.005
Estimated Standard Error Parameter 4			0.010	

No bias appears in the teacher and school effects as the EiV model seems to always recover their true values. The coverage rates for the teacher and school effects are all very close to their nominal values.

Table 6. Unbiasedness Bias of the Random Effects

	Simple/Baseline	Basic	Two Lags	Small Effects
Observed bias: Teacher	0.001	0.000	0.001	0.000
Observed bias: School		0.001	0.000	0.000
Sampling error: mean SE: Teacher	0.127	0.166	0.199	0.124
Sampling error: mean SE: School		0.110	0.114	0.061
Sampling error: standard deviation of SEs: Teacher	0.014	0.034	0.039	0.020
Sampling error: standard deviation of SEs: School		0.032	0.033	0.017
Sampling error: average min SE: Teacher	0.096	0.110	0.134	0.087
Sampling error: average min SE: School		0.070	0.072	0.039
Sampling error: average max SE: Teacher	0.203	0.418	0.436	0.221
Sampling error: average max SE: School		0.247	0.254	0.134
Combined bias and sampling error: Teacher	0.132	0.172	0.206	0.127
Combined bias and sampling error: School		0.114	0.117	0.063
Percentage outside estimated 95% confidence interval: Teacher	5.643	5.366	5.371	5.298
Percentage outside estimated 95% confidence interval: School		4.972	4.866	5.104
Percentage outside estimated 90% confidence interval: Teacher	10.972	10.586	10.568	10.386
Percentage outside estimated 90% confidence interval: School		9.707	9.764	10.152

Conclusion

As described earlier, the State of Florida has committed to the use of a value-added model as one component of its statewide teacher evaluation system as required by the Student Success Act of 2011 [Senate Bill 736], as well as its Race to the Top plan.

With input from an advisory committee (the SGIC), the state selected a value-added model to be used with statewide assessments. The committee and the state began their work with a broad survey of the types of value-added and student growth models currently in use around the country. The committee then narrowed its focus to a set of value-added models which it felt could best illustrate the nature of student, teacher, and school interactions and was flexible in its ability to describe teacher effects and school components. The committee and the state then used information from analysis of 120 different model variants to inform their decision on a statewide value-added model, reviewing data on model precision, explanatory power, and other information.

The selected statewide value-added model design represents the consensus of the committee about the factors that influence student learning which should be taken into consideration in order to produce a fair and accurate estimate of individual teacher and school effectiveness. It also represents the consensus of the group about how best to represent the relationships between students, teachers, and schools in a statistical model.

While the selection of the value-added model to be used with statewide assessments represents one step along the path to a comprehensive teacher evaluation system, much work remains to be done.

For example, the value-added model described in this technical report is applied to the Florida Comprehensive Assessment Test (FCAT) in reading and mathematics across grades 3 through 10. Moving forward, data from new and additional assessments will be analyzed and any necessary modifications to the existing value-added methodology to accommodate these new data will be made. Specifically, data from new end-of-course assessments as well as the statewide alternate assessment will be analyzed in order to produce measures of teacher effectiveness for more teachers. Similarly, the state will consider how other commonly used assessments (such as Advanced Placement) may be utilized with the existing statewide value-added model methodology. Information on the results of value-added analysis using these assessments will be published in future technical documents.

In addition, key decisions about how to report and use information from the statewide value-added model must be made. For 2011-12, each local school district will determine how to use value-added scores in its teacher evaluation system. To assist districts and to comply with state law which requires that three years of teacher value-added data be used in making evaluation decisions, the state will need to provide guidance on a method to aggregate scores across years (and potentially across subjects or grades), so that districts can easily use value-added data in their evaluation systems. Moving forward, the state may also need to provide additional guidance on how best to use value-added data to classify teachers into performance categories (e.g. highly effective, effective, and so on).

Finally, while this document provides detailed information about the value-added methodology for a technical audience, the state will now embark upon efforts to ensure that teachers, principals, district officials, and the public have an understanding of the statewide value-added model and how it estimates teacher and school effectiveness.

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APPENDIX A. SGIC MEMBER ROSTER

The names and affiliations of the SGIC members are as follows:

- **Sam Foerster, Chair,** Associate Superintendent, Putnam
- **Sandi Acosta**, Teacher (6th and 7th Science), Dade
- **Ronda Bourn**, Consortium Administrator
- **Anna Brown**, Representative for Superintendent MaryEllen Elia, Hillsborough
- **Joseph Camputaro**, Teacher (Elementary/Reading), Lee
- **Julia Carson**, Teacher (HS AP History, Geography), Volusia
- **Cathy Cavanaugh**, Postsecondary, UF
- **Doretha Wynn Edgecomb**, School Board, Hillsborough
- **Gisela Field**, District Administrator – Assessment, Dade
- **Stacey Frakes**, Teacher (3rd – 5th ESE), Madison
- **Arlene Ginn**, Teacher (7th Science), Orange
- **Stephanie Hall**, School-based Administrator (ES), Brevard
- **Lavetta B. Henderson**, Postsecondary, FAMU
- **Eric O. Hernandez**, Teacher (Honors Math), Dade
- **Linda J. Kearschner**, Parent, Pinellas
- **Latha Krishnaiyer**, State PTA
- **John le Tellier**, Teacher (Music), Marion
- **Nicole Marsala**, Teacher (8th History), Broward
- **Lisa Maxwell**, Local Union, Broward
- **Lawrence Morehouse**, Business
- **Jeff Murphy**, District Administrator - Student Services, Virtual School
- **Maria Cristina Noya**, School-based Administrator (HS), St. Lucie
- **Pam Stewart**, Assistant Superintendent, St. Johns
- **Lance J. Tomei**, Postsecondary, UCF
- **Gina Tovine**, District Administrator – HR, Levy
- **Lori Westphal**, Teacher (ESE), Lake
- **Tamar E. Woodhouse-Young**, Teacher (High School Math), Duval

Appendix B. Florida Course Codes Used in the Value-Added Model

Table 1. Course Codes Used in the Mathematics Value-Added Model

Year	Course Number	Course Name
2008-09, 2009-10, 2010-11	1200300	Pre-Algebra
2008-09, 2009-10, 2010-11	1200310	Algebra I
2008-09, 2009-10, 2010-11	1200320	Algebra I Honors
2008-09, 2009-10, 2010-11	1200330	Algebra II
2008-09, 2009-10, 2010-11	1200340	Algebra II Honors
2008-09, 2009-10, 2010-11	1200370	Algebra Ia
2008-09, 2009-10, 2010-11	1200380	Algebra Ib
2008-09, 2009-10, 2010-11	1200400	Intensive Mathematics
2008-09, 2009-10, 2010-11	1200410	Math for College Success
2008-09, 2009-10, 2010-11	1200500	Advanded Algebra with Financial Applications
2008-09, 2009-10, 2010-11	1200700	Math College Readiness
2008-09, 2009-10, 2010-11	1201300	Math Analysis
2008-09, 2009-10, 2010-11	1202371	Pre-AICE Additional Math III
2008-09, 2009-10, 2010-11	1204000	M/J Intensive Mathematics (MC)
2008-09, 2009-10, 2010-11	1205010	M/J Mathematics 1
2008-09, 2009-10, 2010-11	1205020	M/J Mathematics 1, Advanced
2008-09, 2009-10, 2010-11	1205040	M/J Mathematics 2
2008-09, 2009-10, 2010-11	1205050	M/J Mathematics 2, Advanced
2008-09, 2009-10, 2010-11	1205070	M/J Mathematics 3
2008-09, 2009-10, 2010-11	1205080	M/J Mathematics 3, Advanced
2008-09, 2009-10, 2010-11	1205090	M/J Mathematics IB
2008-09, 2009-10, 2010-11	1205100	M/J Pre-algebra IB
2008-09, 2009-10, 2010-11	1205370	Consumer Mathematics
2008-09, 2009-10, 2010-11	1205400	Applied Mathematics I
2008-09, 2009-10, 2010-11	1205410	Applied Mathematics II
2008-09, 2009-10, 2010-11	1205500	Explorations in Mathematics I
2008-09, 2009-10, 2010-11	1205510	Explorations in Mathematics II
2008-09, 2009-10, 2010-11	1205540	Business Mathematics
2008-09, 2009-10, 2010-11	1206300	Informal Geometry
2008-09, 2009-10, 2010-11	1206310	Geometry
2008-09, 2009-10, 2010-11	1206320	Geometry Honors
2008-09, 2009-10, 2010-11	1207310	Integrated Mathematics I
2008-09, 2009-10, 2010-11	1207320	Integrated Mathematics II
2008-09, 2009-10, 2010-11	1207330	Integrated Mathematics III
2008-09, 2009-10, 2010-11	1209810	Pre-AICE Mathematics I
2008-09, 2009-10, 2010-11	1209820	Pre-AICE Mathematics II
2008-09	1298010	M/J Great Explorations in Math (GEM) 6th Pre-Algebra
2008-09	1298020	M/J Great Explorations in Math (GEM) 7th Algebra
2008-09	1298030	M/J Great Explorations in Math (GEM) 8th Geometry
2008-09	5012000	Mathematics-Elementary
2008-09	5012010	Functional Basic Skills in Mathematics-Elementary
2008-09, 2009-10, 2010-11	5012020	Math Grade K
2008-09, 2009-10, 2010-11	5012030	Math Grade 1
2008-09, 2009-10, 2010-11	5012040	Math Grade 2
2008-09, 2009-10, 2010-11	5012050	Math Grade 3
2008-09, 2009-10, 2010-11	5012060	Math Grade 4
2008-09, 2009-10, 2010-11	5012070	Math Grade 5
2008-09, 2009-10, 2010-11	7712010	Mathematics K-5
2008-09, 2009-10, 2010-11	7755010	Academics K-5
2008-09, 2009-10, 2010-11	7755030	Academic Skills K-5
2008-09, 2009-10, 2010-11	7755040	Advanced Academic Skills K-5
2008-09, 2009-10, 2010-11	7755050	Developmental Skills K-5
2008-09, 2009-10, 2010-11	7812010	Mathematics: 6-8
2008-09, 2009-10, 2010-11	7855010	Academics 6-8
2008-09, 2009-10, 2010-11	7855030	Academic Skills 6-8
2008-09, 2009-10, 2010-11	7855040	Advanced Academics 6-8
2008-09, 2009-10, 2010-11	7855050	Developmental Skills 6-8
2008-09, 2009-10, 2010-11	7912050	Mathematics 9-12
2008-09, 2009-10, 2010-11	7912340	Life Skills Math: 9-12
2008-09	129800A	M/J Great Explorations in Math (GEM) 6th Pre-Algebra
2008-09	129800B	M/J Great Explorations in Math (GEM) 7th Algebra
2008-09	129800C	M/J Great Explorations in Math (GEM) 8th Geometry

Table 2. Course Codes Used in the Reading Value-Added Model

Year	Course Number	Course Name
2008-09, 2009-10, 2010-11	1000000	M/J Intensive Language Arts (MC)
2008-09, 2009-10, 2010-11	1000010	M/J Intensive Reading (MC)
2009-10, 2010-11	1000020	M/J Intensive Reading and Career Planning
2008-09, 2009-10, 2010-11	1000400	Intensive Language Arts
2008-09, 2009-10, 2010-11	1000410	Intensive Reading
2008-09, 2009-10, 2010-11	1001010	M/J Language Arts 1
2008-09, 2009-10, 2010-11	1001020	M/J Language Arts, 1 Adv.
2008-09, 2009-10, 2010-11	1001030	M/J Language Arts 1, International Baccalaureate
2008-09, 2009-10, 2010-11	1001040	M/J Language Arts 2
2008-09, 2009-10, 2010-11	1001050	M/J Langague Arts 2, Adv
2008-09, 2009-10, 2010-11	1001060	M/J Language Arts 2, International Baccalaureate
2008-09, 2009-10, 2010-11	1001070	M/J Language Arts 3
2008-09, 2009-10, 2010-11	1001080	M/J Language Arts 3, Adv
2008-09, 2009-10, 2010-11	1001090	M/J Language Arts 3,International Baccalaureate
2008-09, 2009-10, 2010-11	1001300	English Skills I
2008-09, 2009-10, 2010-11	1001310	English I
2008-09, 2009-10, 2010-11	1001320	English Honors I
2008-09, 2009-10, 2010-11	1001330	English Skills II
2008-09, 2009-10, 2010-11	1001340	English II
2008-09, 2009-10, 2010-11	1001350	English Honors II
2008-09, 2009-10, 2010-11	1001440	Business English I
2008-09, 2009-10, 2010-11	1001450	Business English II
2008-09, 2009-10, 2010-11	1001560	Pre-AICE English Language
2008-09, 2009-10, 2010-11	1001800	English I Pre-International Baccalaureate
2008-09, 2009-10, 2010-11	1001810	English II Pre-International Baccalaureate
2009-10, 2010-11	1001840	IB Middle Years Program English I
2009-10, 2010-11	1001845	IB Middle Years Program English II
2008-09, 2009-10, 2010-11	1002000	M/J Language Arts 1 through ESOL
2008-09, 2009-10, 2010-11	1002010	M/J Langague Arts 2 through ESOL
2008-09, 2009-10, 2010-11	1002020	M/J Langague Arts 3 through ESOL
2008-09, 2009-10, 2010-11	1002180	M/J Developmental Language Arts Through ESOL (MC)
2008-09, 2009-10, 2010-11	1002300	English I through ESOL
2008-09, 2009-10, 2010-11	1002310	English II through ESOL
2008-09, 2009-10, 2010-11	1002380	Developmental Language Arts Through ESOL
2008-09, 2009-10, 2010-11	1005375	AICE English Literature II
2008-09, 2009-10, 2010-11	1008010	M/J Reading 1
2008-09, 2009-10, 2010-11	1008020	M/J Reading 1, Advanced
2008-09, 2009-10, 2010-11	1008040	M/J Reading 2
2008-09, 2009-10, 2010-11	1008050	M/J Reading 2, Advanced
2008-09, 2009-10, 2010-11	1008070	M/J Reading 3
2008-09, 2009-10, 2010-11	1008080	M/J Reading, Advanced
2008-09, 2009-10, 2010-11	1008300	Reading I
2008-09, 2009-10, 2010-11	1008310	Reading II
2008-09, 2009-10, 2010-11	1008320	Advanced Reading
2008-09, 2009-10, 2010-11	1008330	Reading III
2009-10, 2010-11	1008350	Reading for College Success
2008-09, 2009-10, 2010-11	2400000	Sixth Grade
2008-09, 2009-10, 2010-11	5010010	ESOL English for Speakers of Other Language-Elementary
2008-09, 2009-10, 2010-11	5010020	Functional Basic Skills in Reading-Elementary
2008-09, 2009-10, 2010-11	5010040	Language Arts-Elementary
2008-09, 2009-10, 2010-11	5010050	Reading-Elementary
2008-09, 2009-10, 2010-11	5010060	Integrated Language Arts-Elementary
2008-09, 2009-10, 2010-11	7710010	Language Arts K-5
2008-09, 2009-10, 2010-11	7755010	Academics K-5
2008-09, 2009-10, 2010-11	7755030	Academic Skills K-5
2008-09, 2009-10, 2010-11	7755040	Advanced Academic Skills K-5
2008-09, 2009-10, 2010-11	7755050	Developmental Skills K-5
2008-09, 2009-10, 2010-11	7810010	Language Arts 6-8
2008-09, 2009-10, 2010-11	7810020	Reading: 6-8
2008-09, 2009-10, 2010-11	7910100	Reading 9-12
2008-09, 2009-10, 2010-11	7910110	English 9-12
2008-09, 2009-10, 2010-11	7910400	Life Skills Reading: 9-12

APPENDIX C. FIXED EFFECT ESTIMATES

Table 1. Fixed Effects: Grade 4 Reading, 2010-11

Effect Name	Effect	Standard Error
Constant Term	473.28948	8.0715626
Language Impaired	-39.4393	2.9372883
Deaf or Hard of Hearing	-27.50033	28.293731
Visually Impaired	-28.16003	37.685257
Emotional/Behavioral Disability	-35.36919	19.751021
Specific Learning Disability	-19.5479	7.6782468
Dual-Sensory Impaired	440.46932	162.78546
Autism Spectrum Disorder	-31.81469	23.498643
Traumatic Brain Injured	-111.7807	109.87965
Other Health Impaired	-20.60731	11.333652
Intellectual Disability	-20.89978	66.478877
Enrolled in 2 or more Courses	15.374322	1.9531732
Enrolled in 3 or more Courses	9.2376157	2.1903717
Enrolled in 4 or more Courses	4.8796442	6.7319318
Enrolled in 5 or more Courses	-9.118334	51.884447
Homogeneity of Class 1 Prior Year Test Scores	-0.02008	0.0047442
Homogeneity of Class 2 Prior Year Test Scores	0.0104382	0.0056998
Missing Homogeneity of Class 2 Prior Year Test Scores	11.82098	2.7854498
Homogeneity of Class 3 Prior Year Test Scores	0.0130847	0.0074043
Missing Homogeneity of Class 3 Prior Year Test Scores	12.01265	3.1546793
Homogeneity of Class 4 Prior Year Test Scores	-0.000488	0.009586
Missing Homogeneity of Class 4 Prior Year Test Scores	5.697259	3.8949402
Homogeneity of Class 5 Prior Year Test Scores	0.0079056	0.0137998
Missing Homogeneity of Class 5 Prior Year Test Scores	-0.317121	5.7611271
Homogeneity of Class 6 Prior Year Test Scores	-0.004062	0.0172575
Missing Homogeneity of Class 6 Prior Year Test Scores	8.8996286	6.9670777
Number of Students in Class 1	0.2278213	0.0717638
Number of Students in Class 2	0.0481738	0.0480817
Number of Students in Class 3	0.1072651	0.0536661
Number of Students in Class 4	0.0479365	0.048687
Number of Students in Class 5	0.0778484	0.0880728
Number of Students in Class 6	0.1417139	0.0972198
Difference from Modal Age	-37.26063	0.859862
Gifted Student Indicator	29.853091	9.4171472
English Language Learner Indicator	7.5884046	1.72676
Achievement: Prior Year	0.7765228	0.0020639

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 2. Fixed Effects: Grade 5 Reading, 2010-11

Effect Name	Effect	Standard Error
Constant Term	252.75592	8.2825155
Language Impaired	-0.068282	3.1538825
Deaf or Hard of Hearing	4.2685377	22.992432
Visually Impaired	7.2936619	40.758719
Emotional/Behavioral Disability	-6.43652	19.422141
Specific Learning Disability	-1.207555	8.3594024
Autism Spectrum Disorder	-8.932585	22.48474
Other Health Impaired	-4.253669	10.83725
Intellectual Disability	8.4749104	72.253255
Enrolled in 2 or more Courses	6.048231	1.8277423
Enrolled in 3 or more Courses	6.6678138	2.1180171
Enrolled in 4 or more Courses	1.4545273	6.5435769
Enrolled in 5 or more Courses	7.0551798	40.711496
Homogeneity of Class 1 Prior Year Test Scores	0.0006298	0.0048649
Homogeneity of Class 2 Prior Year Test Scores	0.0050958	0.0059813
Missing Homogeneity of Class 2 Prior Year Test Scores	-0.974422	2.7331346
Homogeneity of Class 3 Prior Year Test Scores	0.0064745	0.0076982
Missing Homogeneity of Class 3 Prior Year Test Scores	0.2868653	3.0383583
Homogeneity of Class 4 Prior Year Test Scores	0.0015222	0.0099288
Missing Homogeneity of Class 4 Prior Year Test Scores	5.0598005	3.7625568
Homogeneity of Class 5 Prior Year Test Scores	0.0056336	0.0142427
Missing Homogeneity of Class 5 Prior Year Test Scores	-3.688758	5.464738
Homogeneity of Class 6 Prior Year Test Scores	0.0118324	0.0193209
Missing Homogeneity of Class 6 Prior Year Test Scores	11.674921	7.1307045
Number of Students in Class 1	-0.431434	0.0750854
Number of Students in Class 2	-0.174729	0.0544604
Number of Students in Class 3	0.0886944	0.0537982
Number of Students in Class 4	0.0710203	0.0476787
Number of Students in Class 5	0.0593746	0.0717484
Number of Students in Class 6	-0.072224	0.1072331
Difference from Modal Age	-21.74667	0.8452812
Gifted Student Indicator	26.52585	9.6284085
English Language Learner Indicator	11.680456	9.0500104
Achievement: Two Years Prior	0.6157219	0.0049343
Achievement: Prior Year	0.2871829	0.004357

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 3. Fixed Effects: Grade 6 Reading, 2010-11

Effect Name	Effect	Standard Error
Constant Term	185.10109	15.220935
Language Impaired	-32.91874	3.6205578
Deaf or Hard of Hearing	-28.71749	25.055512
Visually Impaired	16.344463	37.652171
Emotional/Behavioral Disability	2.7502393	18.314297
Specific Learning Disability	-6.467666	7.5383492
Autism Spectrum Disorder	39.791119	23.979703
Traumatic Brain Injured	158.05119	114.06117
Other Health Impaired	-5.135172	10.794594
Intellectual Disability	-15.67955	58.345302
Enrolled in 2 or more Courses	40.76035	2.3361209
Enrolled in 3 or more Courses	7.2954953	2.7675227
Enrolled in 4 or more Courses	-18.52449	7.2056249
Enrolled in 5 or more Courses	71.71239	31.914473
Enrolled in 6 or more Courses	-103.1539	112.03514
Homogeneity of Class 1 Prior Year Test Scores	-0.024383	0.0045525
Homogeneity of Class 2 Prior Year Test Scores	0.0301148	0.0053888
Missing Homogeneity of Class 2 Prior Year Test Scores	22.500493	3.4804005
Homogeneity of Class 3 Prior Year Test Scores	0.0372126	0.0085022
Missing Homogeneity of Class 3 Prior Year Test Scores	8.8497504	4.0602352
Homogeneity of Class 4 Prior Year Test Scores	0.0056458	0.0125294
Missing Homogeneity of Class 4 Prior Year Test Scores	12.047922	5.8523024
Homogeneity of Class 5 Prior Year Test Scores	-0.002497	0.0208034
Missing Homogeneity of Class 5 Prior Year Test Scores	-13.06623	10.087556
Homogeneity of Class 6 Prior Year Test Scores	0.0428124	0.0305257
Missing Homogeneity of Class 6 Prior Year Test Scores	25.048904	14.439612
Number of Students in Class 1	-0.874086	0.1029611
Number of Students in Class 2	0.1297929	0.1134076
Number of Students in Class 3	0.3681258	0.1602223
Number of Students in Class 4	0.2682621	0.2239495
Number of Students in Class 5	-0.280473	0.3691364
Number of Students in Class 6	0.3128181	0.5480409
Difference from Modal Age	-28.68192	0.7866967
Gifted Student Indicator	26.235894	10.593017
English Language Learner Indicator	-7.396306	11.468293
Achievement: Two Years Prior	0.5456652	0.0060109
Achievement: Prior Year	0.3795654	0.005862

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 4. Fixed Effects: Grade 7 Reading, 2010-11

Effect Name	Effect	Standard Error
Constant Term	155.36374	15.110568
Language Impaired	-14.22913	3.5817283
Deaf or Hard of Hearing	-21.30903	24.847463
Visually Impaired	-61.33771	33.697251
Emotional/Behavioral Disability	-51.91055	12.863482
Specific Learning Disability	-13.15411	6.5911623
Autism Spectrum Disorder	-31.21389	23.337236
Traumatic Brain Injured	53.361827	84.280827
Other Health Impaired	-5.524142	10.45156
Intellectual Disability	66.627656	63.863361
Enrolled in 2 or more Courses	67.194367	2.0401473
Enrolled in 3 or more Courses	3.844224	2.7539806
Enrolled in 4 or more Courses	-20.71458	7.3352801
Enrolled in 5 or more Courses	-9.96338	27.142661
Enrolled in 6 or more Courses	202.02481	134.70919
Homogeneity of Class 1 Prior Year Test Scores	-0.027859	0.0040749
Homogeneity of Class 2 Prior Year Test Scores	0.0462148	0.0051846
Missing Homogeneity of Class 2 Prior Year Test Scores	16.694914	3.0635009
Homogeneity of Class 3 Prior Year Test Scores	0.0362593	0.0078308
Missing Homogeneity of Class 3 Prior Year Test Scores	3.3079391	3.7958
Homogeneity of Class 4 Prior Year Test Scores	0.0217078	0.0124716
Missing Homogeneity of Class 4 Prior Year Test Scores	23.07053	5.8059018
Homogeneity of Class 5 Prior Year Test Scores	-0.000865	0.0213881
Missing Homogeneity of Class 5 Prior Year Test Scores	-11.55677	9.8111999
Homogeneity of Class 6 Prior Year Test Scores	0.0287411	0.0317961
Missing Homogeneity of Class 6 Prior Year Test Scores	25.955701	13.486732
Number of Students in Class 1	-0.901254	0.0962286
Number of Students in Class 2	0.1584682	0.1053166
Number of Students in Class 3	0.2012458	0.1478354
Number of Students in Class 4	0.5972375	0.2255181
Number of Students in Class 5	0.3725754	0.380186
Number of Students in Class 6	0.0998684	0.5126824
Difference from Modal Age	-16.44447	0.6837645
Gifted Student Indicator	-13.15494	9.3731567
English Language Learner Indicator	2.1767832	11.386944
Achievement: Two Years Prior	0.8056186	0.006981
Achievement: Prior Year	0.1295194	0.0053304

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 5. Fixed Effects: Grade 8 Reading, 2010-11

Effect Name	Effect	Standard Error
Constant Term	510.49606	12.002591
Language Impaired	-11.21566	2.9756546
Deaf or Hard of Hearing	-3.18073	16.191602
Visually Impaired	-36.81783	27.275501
Emotional/Behavioral Disability	8.2108367	10.68379
Specific Learning Disability	-9.494328	5.1545126
Autism Spectrum Disorder	6.5841139	16.937298
Traumatic Brain Injured	17.056477	64.747293
Other Health Impaired	-5.090264	7.7142389
Intellectual Disability	-18.16496	50.290433
Enrolled in 2 or more Courses	45.572332	1.5451605
Enrolled in 3 or more Courses	3.0205338	2.1703055
Enrolled in 4 or more Courses	-6.864711	6.0855819
Enrolled in 5 or more Courses	7.5872759	21.488679
Enrolled in 6 or more Courses	29.619999	67.212724
Homogeneity of Class 1 Prior Year Test Scores	-0.041485	0.0036467
Homogeneity of Class 2 Prior Year Test Scores	0.021326	0.0045318
Missing Homogeneity of Class 2 Prior Year Test Scores	11.747275	2.3526687
Homogeneity of Class 3 Prior Year Test Scores	0.0225521	0.0070363
Missing Homogeneity of Class 3 Prior Year Test Scores	8.0094497	3.0045083
Homogeneity of Class 4 Prior Year Test Scores	-0.018295	0.0110015
Missing Homogeneity of Class 4 Prior Year Test Scores	7.8914209	4.3811562
Homogeneity of Class 5 Prior Year Test Scores	-0.00221	0.016882
Missing Homogeneity of Class 5 Prior Year Test Scores	2.6902304	7.6050919
Homogeneity of Class 6 Prior Year Test Scores	0.0349812	0.025556
Missing Homogeneity of Class 6 Prior Year Test Scores	18.131107	10.55741
Number of Students in Class 1	-0.645369	0.0732871
Number of Students in Class 2	0.1659604	0.0810282
Number of Students in Class 3	0.2966507	0.116208
Number of Students in Class 4	0.4030285	0.1651929
Number of Students in Class 5	0.4898653	0.2967227
Number of Students in Class 6	0.1426541	0.4275934
Difference from Modal Age	-20.06601	0.5260609
Gifted Student Indicator	17.720123	8.1612659
English Language Learner Indicator	-1.076096	9.0620833
Achievement: Two Years Prior	0.5882786	0.0061952
Achievement: Prior Year	0.155493	0.0046034

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 6. Fixed Effects: Grade 9 Reading, 2010-11

Effect Name	Effect	Standard Error
Constant Term	127.40448	15.481277
Language Impaired	-0.840678	4.1586213
Deaf or Hard of Hearing	20.680689	19.605202
Visually Impaired	72.171264	28.722217
Emotional/Behavioral Disability	10.658685	12.7573
Specific Learning Disability	4.4612518	6.6694999
Autism Spectrum Disorder	45.555299	24.694002
Traumatic Brain Injured	45.625331	66.069946
Other Health Impaired	-8.687757	10.139713
Intellectual Disability	-24.64518	53.619393
Enrolled in 2 or more Courses	42.961783	1.7596205
Enrolled in 3 or more Courses	4.6682408	2.552918
Enrolled in 4 or more Courses	-14.06406	8.5764983
Enrolled in 5 or more Courses	42.505823	27.673554
Enrolled in 6 or more Courses	-174.0622	59.402781
Homogeneity of Class 1 Prior Year Test Scores	-0.023468	0.0052577
Homogeneity of Class 2 Prior Year Test Scores	0.0193842	0.00667
Missing Homogeneity of Class 2 Prior Year Test Scores	7.9542916	2.6044556
Homogeneity of Class 3 Prior Year Test Scores	0.0365252	0.010047
Missing Homogeneity of Class 3 Prior Year Test Scores	9.3947016	3.5393383
Homogeneity of Class 4 Prior Year Test Scores	0.0239987	0.0155308
Missing Homogeneity of Class 4 Prior Year Test Scores	20.386083	5.3169434
Homogeneity of Class 5 Prior Year Test Scores	0.01049	0.0242804
Missing Homogeneity of Class 5 Prior Year Test Scores	9.8431941	8.7922832
Homogeneity of Class 6 Prior Year Test Scores	-0.002731	0.0356633
Missing Homogeneity of Class 6 Prior Year Test Scores	0.1967386	12.657417
Number of Students in Class 1	-0.158205	0.0611601
Number of Students in Class 2	-0.125701	0.0716625
Number of Students in Class 3	0.296568	0.1122744
Number of Students in Class 4	0.4773906	0.1716203
Number of Students in Class 5	0.4525574	0.2796822
Number of Students in Class 6	0.3730067	0.3957175
Difference from Modal Age	-21.6227	0.6116351
Gifted Student Indicator	27.458593	10.206285
English Language Learner Indicator	10.889199	11.509281
Achievement: Two Years Prior	0.5935253	0.0088751
Achievement: Prior Year	0.3535465	0.0062352

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 7. Fixed Effects: Grade 10 Reading, 2010-11

Effect Name	Effect	Standard Error
Constant Term	-431.1881	18.092754
Language Impaired	-9.97231	5.2509912
Deaf or Hard of Hearing	-61.10017	26.715485
Visually Impaired	-45.68315	51.321393
Emotional/Behavioral Disability	-42.64233	16.004993
Specific Learning Disability	-19.17554	8.1293353
Autism Spectrum Disorder	57.924234	31.22077
Traumatic Brain Injured	81.188052	69.734566
Other Health Impaired	0.4199884	12.199827
Intellectual Disability	-108.7019	71.258538
Enrolled in 2 or more Courses	62.059688	2.5594101
Enrolled in 3 or more Courses	-2.129742	2.9216503
Enrolled in 4 or more Courses	-5.015117	10.434636
Enrolled in 5 or more Courses	-79.8523	49.90915
Enrolled in6or more Courses	98.073897	187.10616
Homogeneity of Class 1 Prior Year Test Scores	0.0255874	0.0058464
Homogeneity of Class 2 Prior Year Test Scores	0.0387735	0.0065963
Missing Homogeneity of Class 2 Prior Year Test Scores	-2.880371	3.25385
Homogeneity of Class 3 Prior Year Test Scores	0.038179	0.0094606
Missing Homogeneity of Class 3 Prior Year Test Scores	-9.038722	3.4148536
Homogeneity of Class 4 Prior Year Test Scores	0.02395	0.0148029
Missing Homogeneity of Class 4 Prior Year Test Scores	8.8502043	5.2435971
Homogeneity of Class 5 Prior Year Test Scores	0.027736	0.0261934
Missing Homogeneity of Class 5 Prior Year Test Scores	4.1389856	9.439345
Homogeneity of Class 6 Prior Year Test Scores	0.1421912	0.0423349
Missing Homogeneity of Class 6 Prior Year Test Scores	30.109126	15.091074
Number of Students in Class 1	-0.600012	0.0826493
Number of Students in Class 2	-0.979678	0.0856548
Number of Students in Class 3	-0.690289	0.1184854
Number of Students in Class 4	-0.150025	0.1887817
Number of Students in Class 5	-0.069648	0.3401006
Number of Students in Class 6	-0.588213	0.5329186
Difference from Modal Age	-6.731747	0.7739671
Gifted Student Indicator	-2.162806	12.69541
English Language Learner Indicator	12.944526	15.682365
Achievement: Two Years Prior	0.7324625	0.0094948
Achievement: Prior Year	0.4910035	0.008455

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 8. Fixed Effects: Grade 4 Mathematics, 2010-11

Effect Name	Effect	Standard Error
Constant Term	385.52231	23.339473
Language Impaired	-3.840265	2.2364243
Deaf or Hard of Hearing	-21.92341	20.422514
Visually Impaired	26.419334	30.738627
Emotional/Behavioral Disability	-51.58701	15.515694
Specific Learning Disability	-23.89384	6.052578
Dual-Sensory Impaired	-497.13	251.98334
Autism Spectrum Disorder	-58.00088	17.436335
Traumatic Brain Injured	-252.2642	114.85163
Other Health Impaired	-28.20661	8.6586249
Intellectual Disability	-97.05666	53.59785
Enrolled in 2 or more Courses	3.4989894	2.2309281
Enrolled in 3 or more Courses	-42.03273	18.825657
Enrolled in 4 or more Courses	-368.5785	133.77785
Homogeneity of Class 1 Prior Year Test Scores	-0.003366	0.0050922
Homogeneity of Class 2 Prior Year Test Scores	0.0130493	0.0072015
Missing Homogeneity of Class 2 Prior Year Test Scores	18.333975	2.6051637
Homogeneity of Class 3 Prior Year Test Scores	-0.033051	0.0132369
Missing Homogeneity of Class 3 Prior Year Test Scores	7.3096264	4.5309252
Homogeneity of Class 4 Prior Year Test Scores	0.0325901	0.0223476
Missing Homogeneity of Class 4 Prior Year Test Scores	11.337511	7.6242129
Homogeneity of Class 5 Prior Year Test Scores	-0.001423	0.0440533
Missing Homogeneity of Class 5 Prior Year Test Scores	1.1431406	13.665091
Homogeneity of Class 6 Prior Year Test Scores	0.0607841	0.0630242
Missing Homogeneity of Class 6 Prior Year Test Scores	19.452163	23.807657
Number of Students in Class 1	0.5862114	0.0650804
Number of Students in Class 2	0.2833142	0.0639089
Number of Students in Class 3	0.3276935	0.0830953
Number of Students in Class 4	0.0899391	0.202489
Number of Students in Class 5	-0.153449	0.1965843
Number of Students in Class 6	0.8720985	1.0114603
Difference from Modal Age	-20.85472	0.6392342
Gifted Student Indicator	-10.81665	7.4334099
English Language Learner Indicator	17.323791	1.2702079
Achievement: Prior Year	0.7604199	0.0019948

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 9. Fixed Effects: Grade 5 Mathematics, 2010-11

Effect Name	Effect	Standard Error
Constant Term	244.23767	19.500574
Language Impaired	-5.669853	2.3171212
Deaf or Hard of Hearing	6.1600951	17.802791
Visually Impaired	-28.47642	27.251441
Emotional/Behavioral Disability	-29.07742	14.503526
Specific Learning Disability	-21.68291	6.1518216
Autism Spectrum Disorder	-42.1806	17.442558
Other Health Impaired	-12.39181	7.9562714
Intellectual Disability	-93.04941	53.300141
Enrolled in 2 or more Courses	-1.319687	2.0525284
Enrolled in 3 or more Courses	20.84478	16.691847
Enrolled in 4 or more Courses	-64.8428	154.72298
Homogeneity of Class 1 Prior Year Test Scores	-0.018824	0.0054563
Homogeneity of Class 2 Prior Year Test Scores	0.007351	0.0075638
Missing Homogeneity of Class 2 Prior Year Test Scores	11.534341	2.4500363
Homogeneity of Class 3 Prior Year Test Scores	-0.021399	0.0137758
Missing Homogeneity of Class 3 Prior Year Test Scores	6.6551091	4.2433632
Homogeneity of Class 4 Prior Year Test Scores	-0.068602	0.0222075
Missing Homogeneity of Class 4 Prior Year Test Scores	-9.904653	7.2831844
Homogeneity of Class 5 Prior Year Test Scores	0.0366288	0.0416947
Missing Homogeneity of Class 5 Prior Year Test Scores	34.326822	14.746744
Homogeneity of Class 6 Prior Year Test Scores	-0.179657	0.051917
Missing Homogeneity of Class 6 Prior Year Test Scores	-16.93585	20.531083
Number of Students in Class 1	0.4621061	0.0578507
Number of Students in Class 2	0.2718567	0.0651857
Number of Students in Class 3	0.3214984	0.0771496
Number of Students in Class 4	0.1247612	0.2014734
Number of Students in Class 5	0.594554	0.4095525
Number of Students in Class 6	0.9489815	0.9697296
Difference from Modal Age	-26.47738	0.640783
Gifted Student Indicator	13.158922	7.0424124
English Language Learner Indicator	-10.76592	6.8759636
Achievement: Two Years Prior	0.7413352	0.0088471
Achievement: Prior Year	0.1605177	0.0070271

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 10. Fixed Effects: Grade 6 Mathematics, 2010-11

Effect Name	Effect	Standard Error
Constant Term	215.16926	39.42855
Language Impaired	-3.578054	2.7135199
Deaf or Hard of Hearing	3.2325699	18.248699
Visually Impaired	-37.44276	28.841561
Emotional/Behavioral Disability	-12.15046	14.321627
Specific Learning Disability	-12.04852	5.7694111
Autism Spectrum Disorder	38.644588	17.710852
Traumatic Brain Injured	67.820831	90.205902
Other Health Impaired	-19.99248	8.3185141
Intellectual Disability	-49.41435	50.290204
Enrolled in 2 or more Courses	36.344955	1.5058887
Enrolled in 3 or more Courses	-1.163721	5.4352515
Enrolled in 4 or more Courses	-31.85544	44.447289
Homogeneity of Class 1 Prior Year Test Scores	-0.037142	0.0048198
Homogeneity of Class 2 Prior Year Test Scores	0.0060841	0.0075158
Missing Homogeneity of Class 2 Prior Year Test Scores	26.98604	2.7512198
Homogeneity of Class 3 Prior Year Test Scores	0.0182785	0.0148413
Missing Homogeneity of Class 3 Prior Year Test Scores	21.803727	5.1053418
Homogeneity of Class 4 Prior Year Test Scores	-0.013219	0.0289149
Missing Homogeneity of Class 4 Prior Year Test Scores	1.9647595	9.4642018
Homogeneity of Class 5 Prior Year Test Scores	-0.044526	0.0716354
Missing Homogeneity of Class 5 Prior Year Test Scores	-3.504406	25.140907
Homogeneity of Class 6 Prior Year Test Scores	0.226856	0.1573563
Missing Homogeneity of Class 6 Prior Year Test Scores	-5.989918	43.07707
Number of Students in Class 1	0.0546773	0.0781862
Number of Students in Class 2	0.615998	0.0971443
Number of Students in Class 3	0.5574255	0.1724428
Number of Students in Class 4	0.0252668	0.2912048
Number of Students in Class 5	0.5092225	0.9382771
Number of Students in Class 6	-2.913145	1.5274348
Difference from Modal Age	-19.8003	0.5728757
Gifted Student Indicator	-8.115738	6.748183
English Language Learner Indicator	-14.21651	8.6379161
Achievement: Two Years Prior	0.6654549	0.0069056
Achievement: Prior Year	0.2282401	0.0061245

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 11. Fixed Effects: Grade 7 Mathematics, 2010-11

Effect Name	Effect	Standard Error
Constant Term	501.1168	33.944595
Language Impaired	9.5616769	2.457258
Deaf or Hard of Hearing	-9.17414	17.010014
Visually Impaired	9.9147634	25.406372
Emotional/Behavioral Disability	9.6876221	9.4042094
Specific Learning Disability	2.3947086	4.5619344
Autism Spectrum Disorder	7.1054907	14.804152
Traumatic Brain Injured	89.863986	54.581504
Other Health Impaired	10.473004	7.2771765
Intellectual Disability	-35.94316	45.337656
Enrolled in 2 or more Courses	33.768658	1.1395593
Enrolled in 3 or more Courses	-1.180703	3.8026075
Enrolled in 4 or more Courses	43.180675	62.284664
Homogeneity of Class 1 Prior Year Test Scores	0.0010888	0.0035572
Homogeneity of Class 2 Prior Year Test Scores	0.0190724	0.0056438
Missing Homogeneity of Class 2 Prior Year Test Scores	15.814171	2.1687938
Homogeneity of Class 3 Prior Year Test Scores	0.0192297	0.0113031
Missing Homogeneity of Class 3 Prior Year Test Scores	10.617272	3.9666914
Homogeneity of Class 4 Prior Year Test Scores	-0.000129	0.0226006
Missing Homogeneity of Class 4 Prior Year Test Scores	-4.832015	7.504312
Homogeneity of Class 5 Prior Year Test Scores	-0.015029	0.0468479
Missing Homogeneity of Class 5 Prior Year Test Scores	7.9309564	18.191022
Homogeneity of Class 6 Prior Year Test Scores	0.0312502	0.0983872
Missing Homogeneity of Class 6 Prior Year Test Scores	9.516115	34.765109
Number of Students in Class 1	-0.151885	0.0596904
Number of Students in Class 2	0.38913	0.0782597
Number of Students in Class 3	0.1892102	0.1344612
Number of Students in Class 4	-0.012136	0.233502
Number of Students in Class 5	0.2395993	0.6105321
Number of Students in Class 6	-0.057593	1.1487586
Difference from Modal Age	-10.88687	0.4390447
Gifted Student Indicator	-0.215478	5.1783613
English Language Learner Indicator	4.0689656	7.498834
Achievement: Two Years Prior	0.6764783	0.0053744
Achievement: Prior Year	0.0767584	0.004823

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 12. Fixed Effects: Grade 8 Mathematics, 2010-11

Effect Name	Effect	Standard Error
Constant Term	614.85536	26.888289
Language Impaired	10.803628	2.066494
Deaf or Hard of Hearing	18.824003	11.071911
Visually Impaired	32.532385	23.114175
Emotional/Behavioral Disability	-6.132018	7.7828823
Specific Learning Disability	10.275597	3.6454513
Autism Spectrum Disorder	15.834316	11.482713
Traumatic Brain Injured	5.2355106	43.167249
Other Health Impaired	2.3817283	5.5117007
Intellectual Disability	28.355891	65.253012
Enrolled in 2 or more Courses	14.956464	0.8741064
Enrolled in 3 or more Courses	-3.561152	2.5547497
Enrolled in 4 or more Courses	44.973758	20.952594
Homogeneity of Class 1 Prior Year Test Scores	0.0059785	0.0033737
Homogeneity of Class 2 Prior Year Test Scores	0.0303504	0.0050766
Missing Homogeneity of Class 2 Prior Year Test Scores	20.774805	1.5353988
Homogeneity of Class 3 Prior Year Test Scores	0.0190157	0.009875
Missing Homogeneity of Class 3 Prior Year Test Scores	-0.376343	2.83383
Homogeneity of Class 4 Prior Year Test Scores	0.0152513	0.0178199
Missing Homogeneity of Class 4 Prior Year Test Scores	6.5615044	5.0576898
Homogeneity of Class 5 Prior Year Test Scores	-0.041089	0.0490118
Missing Homogeneity of Class 5 Prior Year Test Scores	-8.998075	11.911559
Homogeneity of Class 6 Prior Year Test Scores	0.121444	0.0961515
Missing Homogeneity of Class 6 Prior Year Test Scores	55.356039	27.527077
Number of Students in Class 1	-0.085874	0.0472429
Number of Students in Class 2	0.6632629	0.0558654
Number of Students in Class 3	0.1601729	0.0990379
Number of Students in Class 4	0.2032172	0.171318
Number of Students in Class 5	-0.295691	0.3921755
Number of Students in Class 6	2.2442624	0.9671986
Difference from Modal Age	-6.128462	0.3385457
Gifted Student Indicator	9.8469445	4.5067393
English Language Learner Indicator	-4.747537	5.9790561
Achievement: Two Years Prior	0.5845132	0.0058883
Achievement: Prior Year	0.0932135	0.004312

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

Table 13. Fixed Effects: Grade 10 Mathematics, 2010-11

Effect Name	Effect	Standard Error
Constant Term	281.31535	14.591631
Language Impaired	9.2714132	1.9721118
Deaf or Hard of Hearing	12.113933	9.5204873
Visually Impaired	3.0800174	25.00785
Emotional/Behavioral Disability	8.2883581	5.8676514
Specific Learning Disability	4.1541961	2.9946882
Autism Spectrum Disorder	1.1327465	9.5835244
Traumatic Brain Injured	-16.96285	37.23783
Other Health Impaired	-4.168503	4.3417563
Intellectual Disability	3.2234818	25.434598
Enrolled in 2 or more Courses	13.796268	0.630254
Enrolled in 3 or more Courses	4.1042532	1.8515109
Enrolled in 4 or more Courses	-22.47413	8.5776429
Enrolled in 5 or more Courses	-119.1727	56.524715
Homogeneity of Class 1 Prior Year Test Scores	-0.016324	0.0023542
Homogeneity of Class 2 Prior Year Test Scores	0.008151	0.0040097
Missing Homogeneity of Class 2 Prior Year Test Scores	8.1471443	0.8601868
Homogeneity of Class 3 Prior Year Test Scores	0.0187226	0.0087236
Missing Homogeneity of Class 3 Prior Year Test Scores	5.9321266	1.9389153
Homogeneity of Class 4 Prior Year Test Scores	0.0042555	0.0150524
Missing Homogeneity of Class 4 Prior Year Test Scores	2.3356358	3.3620025
Homogeneity of Class 5 Prior Year Test Scores	0.080547	0.0322793
Missing Homogeneity of Class 5 Prior Year Test Scores	-0.691126	7.5575477
Homogeneity of Class 6 Prior Year Test Scores	-0.107014	0.0725176
Missing Homogeneity of Class 6 Prior Year Test Scores	-37.2611	14.208512
Number of Students in Class 1	0.2395978	0.0234322
Number of Students in Class 2	0.2956542	0.03489
Number of Students in Class 3	0.2864638	0.0819374
Number of Students in Class 4	0.121552	0.1421114
Number of Students in Class 5	-0.668394	0.3191165
Number of Students in Class 6	-0.891107	0.5996503
Difference from Modal Age	-8.971477	0.252136
Gifted Student Indicator	2.1513553	3.8364851
English Language Learner Indicator	15.791409	5.3689794
Achievement: Two Years Prior	0.6891791	0.0071194
Achievement: Prior Year	0.2085841	0.0061022

*Attendance and mobility variables are not included in the model because the data is not reported until August during the Survey 5 data collection.

APPENDIX D. TEACHER VALUE-ADDED SCORES BY DISTRICT

Table 1. Mean and Standard Deviation of Teacher Value-Added Scores by District: Grade 4, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	-0.79	46.72	147	2.05	21.75	145
BAKER	-16.27	61.56	13	-21.70	21.89	13
BAY	-3.21	51.45	123	3.40	24.29	130
BRADFORD	-25.90	36.54	14	-15.33	13.72	16
BREVARD	4.81	40.24	387	3.17	17.58	416
BROWARD	9.28	43.94	1080	1.89	22.25	1125
CALHOUN	-5.78	20.75	6	-3.34	18.20	8
CHARLOTTE	-8.93	29.88	73	3.65	21.90	77
CITRUS	17.65	36.59	78	4.35	22.98	93
CLAY	-2.60	38.12	167	-2.44	18.86	184
COLLIER	-5.29	45.52	206	-0.56	20.09	253
COLUMBIA	-1.55	34.55	37	-0.11	11.83	38
DADE	4.25	48.92	1250	5.16	26.37	1476
DEAF/BLIND	*	*	3	*	*	3
DESOTO	1.93	45.73	23	-7.25	17.82	24
DIXIE	9.75	40.66	11	-4.67	17.46	16
DUVAL	15.17	44.81	545	-4.20	22.47	571
ESCAMBIA	-0.09	45.97	242	-2.28	21.90	249
FAMU LAB SCH	*	*	2	*	*	2
FAU LAB SCH	12.56	28.12	11	-0.52	19.70	11
FL VIRTUAL	*	*	2	*	*	2
FLAGLER	-20.07	46.72	42	-3.95	22.21	54
FRANKLIN	-0.60	54.70	5	-8.85	34.06	7
FSU LAB SCH	38.37	27.59	11	25.65	8.31	14
GADSDEN	37.92	46.13	28	0.16	31.40	31
GILCHRIST	21.63	59.65	13	10.71	39.09	15
GLADES	-13.48	25.96	8	-3.28	13.30	8
GULF	30.91	45.66	11	1.83	26.02	12
HAMILTON	2.05	38.14	6	-2.51	11.27	10
HARDEE	7.56	37.48	24	-10.64	17.68	29
HENDRY	9.74	36.69	28	-2.09	21.17	31
HERNANDO	-9.45	40.48	105	-3.02	21.65	108
HIGHLANDS	-5.81	45.52	63	-2.30	19.57	71
HILLSBOROUGH	-4.38	41.28	910	2.95	19.84	973
HOLMES	22.93	37.03	14	1.36	33.05	12
INDIAN RIVER	3.26	35.64	78	1.91	20.32	74

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
JACKSON	28.48	45.55	31	12.51	17.59	36
JEFFERSON	11.86	53.72	7	59.02	31.98	7
LAFAYETTE	*	*	4	-7.68	10.41	8
LAKE	-1.48	45.03	190	-4.86	18.12	201
LEE	6.05	42.29	421	1.11	20.67	448
LEON	1.07	35.32	168	-0.57	20.51	173
LEVY	-0.95	27.54	26	-11.18	13.24	31
LIBERTY	-8.69	33.56	6	-3.21	12.49	9
MADISON	-44.39	57.00	12	-5.02	23.96	18
MANATEE	5.36	39.60	230	0.50	19.31	239
MARION	1.39	42.49	199	-6.90	18.76	248
MARTIN	12.60	35.22	79	-1.93	20.89	86
MONROE	18.91	44.62	37	-12.70	18.36	44
NASSAU	10.73	48.33	45	8.05	17.98	48
OKALOOSA	-9.35	35.38	95	-0.61	18.38	127
OKEECHOBEE	2.50	35.05	33	-3.69	23.72	36
ORANGE	-0.25	41.21	848	-2.01	20.48	892
OSCEOLA	-2.99	36.66	229	5.27	17.75	279
PALM BEACH	3.70	43.95	546	7.55	19.76	945
PASCO	-8.16	38.91	361	-6.67	19.36	399
PINELLAS	-10.58	39.92	451	-1.14	19.02	456
POLK	-8.78	39.15	528	-3.79	21.80	531
PUTNAM	27.70	44.18	52	3.47	15.68	94
SANTA ROSA	-1.55	44.22	115	3.16	20.04	119
SARASOTA	-14.76	47.22	174	1.10	21.15	202
SEMINOLE	5.20	36.48	291	0.64	19.20	309
ST. JOHNS	-6.50	39.85	134	7.30	22.94	141
ST. LUCIE	0.34	40.58	187	-10.88	22.02	202
SUMTER	12.38	37.12	27	8.12	24.17	39
SUWANNEE	9.03	37.24	29	-3.83	22.17	29
TAYLOR	-20.71	64.60	8	3.75	29.05	12
UF LAB SCH	*	*	3	*	*	3
UNION	38.39	57.87	12	15.16	15.29	12
VOLUSIA	-8.58	36.80	351	-4.51	17.26	399
WAKULLA	-13.99	49.23	29	2.34	24.85	28
WALTON	10.58	33.68	34	6.33	16.36	36
WASHINGTON	3.63	69.58	15	3.62	24.18	15
State Avg.	1.09	43.25	11734	0.65	21.67	13157

Table 2. Mean and Standard Deviation of Teacher Value-Added Scores by District: Grade 5, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	3.27	39.77	134	1.49	18.60	121
BAKER	-25.54	37.57	12	-22.96	12.38	12
BAY	2.07	39.81	112	1.53	16.07	121
BRADFORD	-7.74	37.28	12	-4.37	16.32	13
BREVARD	0.22	31.51	365	-2.49	14.46	408
BROWARD	5.37	34.11	1021	-1.38	18.32	1060
CALHOUN	3.89	32.97	9	-6.61	11.51	14
CHARLOTTE	-0.79	38.00	59	5.99	17.68	71
CITRUS	9.24	31.08	66	4.19	13.91	83
CLAY	0.03	32.48	132	-3.47	14.47	157
COLLIER	-6.54	36.54	203	-7.09	14.07	229
COLUMBIA	2.10	11.12	13	2.48	9.04	14
DADE	-0.76	43.62	1097	3.46	20.09	1345
DEAF/BLIND	*	*	4	*	*	4
DESOTO	1.11	34.49	19	-17.17	31.51	18
DIXIE	*	*	4	15.04	20.08	7
DUVAL	0.91	35.98	507	-1.35	16.89	548
ESCAMBIA	-3.50	42.86	223	-0.39	18.98	231
FAMU LAB SCH	*	*	2	*	*	2
FAU LAB SCH	17.13	23.53	9	3.00	17.79	11
FL VIRTUAL	*	*	2	*	*	*
FLAGLER	-12.98	41.51	37	5.25	15.55	45
FRANKLIN	*	*	4	-0.78	8.67	6
FSU LAB SCH	4.64	32.07	9	2.32	9.65	9
GADSDEN	25.75	49.31	24	9.58	40.26	24
GILCHRIST	-16.61	51.12	13	9.01	15.92	14
GLADES	-8.40	20.53	5	-17.60	25.51	9
GULF	-16.23	39.92	9	-1.76	15.11	12
HAMILTON	-3.43	32.15	6	-4.43	9.20	10
HARDEE	-4.58	33.90	23	-10.57	12.84	28
HENDRY	10.80	45.25	27	0.37	15.96	30
HERNANDO	-14.58	27.50	99	-3.52	16.23	103
HIGHLANDS	-17.24	39.37	58	-7.38	17.77	62
HILLSBOROUGH	-1.15	30.70	892	1.23	14.73	955
HOLMES	-14.25	49.93	11	3.09	13.35	13
INDIAN RIVER	8.69	30.20	75	-3.57	13.13	74
JACKSON	-20.35	63.69	28	2.57	14.29	35
JEFFERSON	42.80	29.43	8	19.65	25.48	8

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LAFAYETTE	*	*	3	-0.43	9.23	5
LAKE	-2.70	33.34	163	0.27	15.99	182
LEE	12.28	35.84	382	-4.83	15.24	396
LEON	3.41	35.62	168	6.61	20.38	166
LEVY	-15.26	35.33	28	-3.89	12.10	34
LIBERTY	-3.50	32.23	6	21.80	11.33	8
MADISON	-25.25	35.39	11	7.88	17.10	16
MANATEE	8.25	33.15	227	-1.54	12.94	224
MARION	1.28	28.97	168	-3.88	17.51	223
MARTIN	9.28	30.74	70	0.04	13.20	78
MONROE	4.23	24.62	30	-4.46	11.03	38
NASSAU	3.31	28.68	40	-3.29	13.77	46
OKALOOSA	0.80	32.03	85	-1.86	13.32	123
OKEECHOBEE	6.25	47.94	24	-12.38	18.24	32
ORANGE	3.30	32.81	765	1.57	15.66	808
OSCEOLA	8.56	30.42	221	2.99	14.61	276
PALM BEACH	-1.58	34.76	503	3.33	15.40	791
PASCO	2.11	34.72	351	-2.05	15.69	378
PINELLAS	-5.76	37.26	454	-1.69	14.72	455
POLK	-6.68	33.95	532	-1.04	16.62	535
PUTNAM	11.00	32.70	51	-2.44	13.20	77
SANTA ROSA	0.35	35.39	108	4.27	18.56	114
SARASOTA	1.59	40.72	154	4.39	18.43	185
SEMINOLE	3.91	28.51	288	2.48	14.91	292
ST. JOHNS	4.31	33.20	116	9.97	15.92	129
ST. LUCIE	5.06	35.74	165	-0.00	14.44	187
SUMTER	17.85	28.20	21	10.85	14.99	35
SUWANNEE	13.38	22.20	18	3.57	17.56	18
TAYLOR	-33.25	53.33	7	-13.05	13.78	13
UF LAB SCH	*	*	3	*	*	3
UNION	-12.98	43.24	7	-13.81	27.48	7
VOLUSIA	-3.55	33.82	342	-6.55	13.51	366
WAKULLA	1.47	30.03	26	6.22	17.35	26
WALTON	17.49	26.55	32	3.93	12.60	35
WASHINGTON	-80.41	49.25	6	-6.24	12.44	10
State Avg.	0.86	35.82	10878	0.10	16.90	12182

Table 3. Mean and Standard Deviation of Teacher Value-Added Scores by District: Grade 6, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	-5.16	27.18	61	-7.59	14.75	91
BAKER	48.04	34.67	14	2.47	7.84	12
BAY	-2.99	25.79	54	-6.56	14.88	78
BRADFORD	-9.79	30.98	7	-5.76	11.07	14
BREVARD	36.14	27.50	315	7.97	15.54	342
BROWARD	-1.32	24.93	326	2.60	17.24	556
CALHOUN	3.25	23.48	8	-6.47	11.56	10
CHARLOTTE	-12.31	17.58	26	-0.87	17.29	36
CITRUS	-9.70	17.00	35	-17.25	12.82	36
CLAY	19.83	21.58	96	4.26	12.61	126
COLLIER	11.21	20.34	71	9.05	12.94	131
COLUMBIA	-8.09	8.43	8	-13.90	4.63	11
DADE	-10.68	27.72	713	6.70	19.50	962
DEAF/BLIND	*	*	2	*	*	4
DESOTO	-9.52	20.30	10	-18.48	19.71	11
DIXIE	*	*	2	18.43	7.34	5
DUVAL	-15.79	23.49	238	-6.23	15.19	310
ESCAMBIA	-14.76	21.98	78	-13.64	17.14	130
FAMU LAB SCH	*	*	1	*	*	2
FAU LAB SCH	25.14	19.11	7	36.86	10.10	10
FL VIRTUAL	*	*	1	*	*	1
FLAGLER	7.74	19.59	35	6.29	10.88	39
FRANKLIN	-19.56	28.26	5	-6.82	7.60	5
FSU LAB SCH	*	*	3	*	*	3
GADSDEN	0.48	30.31	17	-21.17	25.24	21
GILCHRIST	*	*	3	-4.79	4.22	9
GLADES	*	*	4	-6.38	22.11	8
GULF	-24.32	15.57	6	-2.57	10.35	8
HAMILTON	51.76	42.09	6	-12.47	10.34	12
HARDEE	-12.72	13.12	8	-3.81	12.43	11
HENDRY	-20.22	21.30	9	-19.16	9.51	13
HERNANDO	-8.16	23.09	50	-5.19	12.01	69
HIGHLANDS	15.80	23.80	34	4.36	12.35	39
HILLSBOROUGH	0.31	21.51	328	-11.41	15.50	487
HOLMES	19.04	27.43	10	-5.51	9.28	10
INDIAN RIVER	2.07	17.73	36	-5.84	13.32	46
JACKSON	-12.92	14.31	16	-0.09	14.98	24
JEFFERSON	-3.05	4.82	7	1.00	3.89	5
LAFAYETTE	*	*	1	*	*	1

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LAKE	-2.86	23.76	71	-3.04	15.53	106
LEE	-3.09	24.32	147	-8.99	14.37	229
LEON	3.96	24.10	71	-2.25	14.70	92
LEVY	2.35	22.94	19	-4.99	15.18	26
LIBERTY	24.59	23.12	9	*	*	4
MADISON	-10.83	8.30	6	-15.94	7.57	8
MANATEE	-5.87	23.55	83	-1.38	13.25	114
MARION	-8.16	17.98	77	2.40	12.02	128
MARTIN	3.51	23.57	29	-0.93	9.86	52
MONROE	16.80	17.12	21	10.87	7.67	35
NASSAU	0.32	11.95	22	-6.84	12.12	28
OKALOOSA	4.39	23.78	64	2.23	12.41	57
OKEECHOBEE	8.21	29.59	12	-4.08	11.93	21
ORANGE	-3.84	22.77	223	2.43	14.35	361
OSCEOLA	0.52	22.34	101	7.63	13.57	130
PALM BEACH	2.83	25.50	328	4.14	16.89	392
PASCO	7.57	22.87	137	-2.25	12.15	240
PINELLAS	-13.63	21.62	199	-11.68	15.35	240
POLK	-15.66	22.76	195	-3.85	12.46	304
PUTNAM	-4.22	34.23	26	-18.65	15.53	57
SANTA ROSA	-5.35	20.67	48	0.04	11.22	61
SARASOTA	5.79	25.66	91	8.85	17.63	87
SEMINOLE	-2.06	23.78	118	5.97	11.20	163
ST. JOHNS	1.60	30.63	72	8.91	22.01	65
ST. LUCIE	3.16	23.57	85	1.25	12.30	142
SUMTER	-6.50	30.87	10	-13.14	12.57	23
SUWANNEE	-6.48	12.16	13	0.41	9.28	17
TAYLOR	-0.72	26.67	11	9.68	13.11	12
UF LAB SCH	*	*	1	*	*	3
UNION	-7.34	10.99	5	12.22	6.61	8
VOLUSIA	-10.49	21.84	110	-12.11	11.23	179
WAKULLA	11.12	21.01	15	-10.12	9.07	16
WALTON	19.35	22.34	22	-0.97	15.83	22
WASHINGTON	-8.91	16.85	6	-6.84	13.75	7
State Avg.	-0.88	27.48	5078	-0.66	17.06	7091

Table 4. Mean and Standard Deviation of Teacher Value-Added Scores by District: Grade 7, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	-0.67	16.68	67	-3.14	14.27	94
BAKER	-10.47	9.21	8	7.44	15.42	11
BAY	3.99	17.58	61	-1.22	13.04	75
BRADFORD	-0.16	14.34	9	-5.73	8.21	13
BREVARD	-11.05	16.87	127	-8.52	15.45	152
BROWARD	-3.47	17.47	364	-2.50	17.11	572
CALHOUN	-0.33	14.29	10	-20.01	9.85	15
CHARLOTTE	7.16	18.27	26	8.85	15.42	43
CITRUS	2.54	18.14	44	-11.81	17.09	47
CLAY	-5.83	16.13	65	1.43	12.37	80
COLLIER	7.27	15.77	63	5.15	14.73	123
COLUMBIA	-9.86	11.21	9	2.20	6.88	10
DADE	-0.36	17.77	814	9.27	16.94	996
DEAF/BLIND	*	*	2	*	*	3
DESOTO	-2.02	30.06	12	2.35	14.73	18
DIXIE	-4.40	4.11	5	9.72	10.60	7
DUVAL	1.78	16.26	270	1.98	14.11	342
ESCAMBIA	-3.09	14.89	81	-9.45	17.34	124
FAMU LAB SCH	*	*	1	*	*	2
FAU LAB SCH	-1.62	12.80	7	0.78	5.20	11
FL VIRTUAL	*	*	1	*	*	1
FLAGLER	2.86	14.68	31	-1.50	13.72	29
FRANKLIN	*	*	4	1.99	19.60	7
FSU LAB SCH	*	*	3	*	*	4
GADSDEN	-8.73	14.42	13	-2.92	20.23	19
GILCHRIST	*	*	4	-14.44	9.34	8
GLADES	*	*	4	-15.88	9.33	12
GULF	4.99	13.68	8	-1.32	14.72	9
HAMILTON	*	*	4	-8.41	9.31	5
HARDEE	-14.09	15.68	6	2.20	15.66	10
HENDRY	-6.41	16.39	8	-10.71	16.79	14
HERNANDO	3.08	15.01	51	3.58	13.87	61
HIGHLANDS	8.76	13.44	32	6.09	13.74	35
HILLSBOROUGH	2.92	15.77	383	-5.10	15.39	492
HOLMES	-0.07	19.36	9	-15.91	16.52	19
INDIAN RIVER	4.15	15.47	36	-13.14	17.89	49
JACKSON	-2.06	14.51	17	-9.19	16.35	27
JEFFERSON	-10.52	11.89	7	-0.50	2.24	7
LAFAYETTE	*	*	2	*	*	2

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LAKE	-0.45	15.15	79	-0.09	15.61	112
LEE	7.98	16.16	170	-2.42	16.59	279
LEON	1.22	17.91	94	-0.33	19.44	89
LEVY	1.96	17.47	19	-0.82	22.43	21
LIBERTY	7.75	16.35	9	-13.41	16.52	9
MADISON	0.08	13.16	7	5.99	9.43	10
MANATEE	1.75	14.78	99	1.70	13.53	122
MARION	-1.73	17.77	84	6.80	11.40	136
MARTIN	1.30	14.50	35	-12.17	16.72	50
MONROE	1.38	17.33	25	-2.39	10.67	38
NASSAU	-0.93	15.90	22	5.05	12.53	22
OKALOOSA	2.29	16.10	75	2.78	17.21	68
OKEECHOBEE	2.08	12.45	15	-2.07	15.26	22
ORANGE	3.64	16.88	256	6.11	16.13	338
OSCEOLA	3.97	14.14	111	4.19	15.94	140
PALM BEACH	-0.05	16.22	371	3.32	17.17	421
PASCO	5.20	12.65	146	4.19	11.32	192
PINELLAS	-8.52	14.31	225	-1.64	19.55	237
POLK	-3.90	14.25	220	-6.74	15.37	327
PUTNAM	-5.51	14.65	22	1.29	13.41	37
SANTA ROSA	-1.86	14.98	51	1.89	16.88	50
SARASOTA	1.59	16.87	99	5.90	17.34	94
SEMINOLE	4.84	17.14	148	1.10	14.45	174
ST. JOHNS	5.08	15.21	86	10.04	16.97	73
ST. LUCIE	1.76	15.52	94	-8.89	15.47	138
SUMTER	0.68	16.60	12	-18.06	21.85	23
SUWANNEE	2.50	8.91	12	2.28	11.09	17
TAYLOR	0.85	12.00	12	-13.81	14.40	14
UF LAB SCH	*	*	1	*	*	3
UNION	2.32	12.26	5	21.09	13.83	11
VOLUSIA	-3.62	14.24	145	-13.65	13.92	209
WAKULLA	9.74	18.51	12	-15.28	14.94	17
WALTON	12.40	19.28	18	6.74	14.58	26
WASHINGTON	0.49	15.86	8	-5.20	7.90	12
State Avg.	0.27	16.69	5425	0.23	17.17	7046

Table 5. Mean and Standard Deviation of Teacher Value-Added Scores by District: Grade 8, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	7.73	16.11	62	-0.00	9.98	83
BAKER	-12.59	11.33	8	-0.72	5.50	10
BAY	0.73	18.66	59	-0.48	7.67	71
BRADFORD	-1.00	9.72	7	0.55	5.34	12
BREVARD	-6.50	12.75	132	-4.24	8.32	144
BROWARD	1.62	16.52	351	1.69	11.66	544
CALHOUN	5.53	13.27	10	-6.43	4.02	13
CHARLOTTE	1.49	12.07	26	5.74	9.04	38
CITRUS	2.79	12.12	36	-1.97	11.75	39
CLAY	-0.14	14.60	64	-0.10	7.87	77
COLLIER	7.81	14.22	65	2.68	10.75	115
COLUMBIA	-3.37	7.06	8	-5.58	6.16	11
DADE	2.33	16.15	747	6.68	11.39	917
DEAF/BLIND	*	*	3	-4.79	5.81	6
DESOTO	-6.18	16.26	12	-3.27	6.63	18
DIXIE	*	*	2	2.95	5.24	6
DOZIER/OKEEC	*	*	1	*	*	2
DUVAL	-0.02	14.23	227	3.33	8.65	277
ESCAMBIA	-2.32	13.14	80	-6.24	9.13	133
FAMU LAB SCH	*	*	1	*	*	3
FAU LAB SCH	4.27	16.57	5	9.22	7.35	7
FL VIRTUAL	*	*	1	*	*	2
FLAGLER	-2.15	11.72	30	1.45	9.35	30
FRANKLIN	-11.75	6.21	6	-7.85	5.40	6
FSU LAB SCH	*	*	3	5.50	5.20	5
GADSDEN	4.77	17.31	15	2.46	17.85	17
GILCHRIST	*	*	4	-9.47	3.43	7
GLADES	*	*	3	-10.59	2.81	7
GULF	3.34	14.35	5	-14.65	6.61	5
HAMILTON	-15.02	8.65	5	-8.59	11.48	8
HARDEE	4.09	17.24	6	-8.02	10.49	8
HENDRY	-0.71	15.16	9	-8.91	14.97	15
HERNANDO	-1.62	12.28	52	-3.53	10.14	70
HIGHLANDS	1.35	13.25	36	-0.65	8.71	38
HILLSBOROUGH	-3.43	14.92	348	-4.57	9.56	463
HOLMES	-0.84	12.80	17	-2.88	6.74	19
INDIAN RIVER	-5.22	14.63	36	-8.11	8.08	48
JACKSON	-4.33	12.29	19	-4.70	5.08	23

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
JEFFERSON	*	*	2	*	*	3
LAFAYETTE	*	*	2	*	*	1
LAKE	1.58	11.28	76	0.27	9.58	107
LEE	7.36	17.40	149	-0.72	9.67	243
LEON	3.54	13.37	81	2.84	8.79	85
LEVY	0.37	12.82	20	3.69	12.73	22
LIBERTY	-11.48	6.42	6	-0.68	3.37	8
MADISON	-0.53	9.38	8	-16.73	8.68	12
MANATEE	1.48	12.93	91	-4.81	7.45	114
MARION	2.21	11.94	86	-0.13	7.96	122
MARTIN	3.70	12.09	36	-0.13	7.05	55
MONROE	14.07	14.38	24	1.17	8.91	31
NASSAU	-10.69	12.23	24	5.29	8.55	30
OKALOOSA	3.70	14.09	69	6.11	10.63	68
OKEECHOBEE	-5.18	14.82	15	-7.77	5.84	25
ORANGE	-3.69	15.55	247	1.83	10.34	347
OSCEOLA	3.08	11.90	112	-2.61	10.56	146
PALM BEACH	4.95	14.71	345	4.48	9.70	395
PASCO	0.69	14.44	140	-0.08	8.36	198
PINELLAS	-7.47	14.62	205	-4.36	10.58	212
POLK	-1.01	14.21	185	-5.67	11.49	286
PUTNAM	-5.36	11.54	23	5.35	7.20	31
SANTA ROSA	1.41	15.25	48	3.97	9.39	48
SARASOTA	5.68	15.66	84	0.68	8.52	103
SEMINOLE	5.17	14.33	118	2.14	9.44	148
ST. JOHNS	3.15	13.53	76	7.97	9.12	79
ST. LUCIE	3.77	15.84	86	-5.84	10.43	118
SUMTER	-3.35	10.58	13	-7.34	7.57	25
SUWANNEE	-7.04	12.04	12	-2.70	7.31	11
TAYLOR	4.23	4.91	16	0.82	4.60	16
UF LAB SCH	*	*	1	*	*	2
UNION	2.67	10.49	6	-2.16	5.41	11
VOLUSIA	-1.45	14.15	139	-10.77	9.03	206
WAKULLA	-1.20	10.26	12	-5.89	5.24	20
WALTON	5.52	14.85	24	5.28	11.11	26
WASHINGTON	11.89	18.23	7	-3.50	8.76	12
State Avg.	0.77	15.23	5070	0.16	11.01	6633

Table 6. Mean and Standard Deviation of Teacher Value-Added Scores by District: Grade 9, 2010-11

	Reading		
District	Mean	Std. Dev.	N
ALACHUA	6.63	8.28	59
BAKER	10.78	4.11	13
BAY	1.67	8.03	72
BRADFORD	3.56	4.07	7
BREVARD	5.04	6.56	193
BROWARD	-6.91	8.82	475
CALHOUN	-6.05	2.88	6
CHARLOTTE	3.66	6.83	29
CITRUS	7.36	7.37	44
CLAY	4.19	5.77	92
COLLIER	1.01	8.79	100
COLUMBIA	-0.19	1.30	8
DADE	-0.62	7.99	841
DEAF/BLIND	0.17	4.47	7
DESOTO	-2.91	3.60	30
DIXIE	*	*	3
DOZIER/OKEEC	-2.67	5.46	6
DUVAL	0.14	6.57	293
ESCAMBIA	-2.37	6.38	157
FAMU LAB SCH	*	*	1
FAU LAB SCH	*	*	1
FL VIRTUAL	*	*	1
FLAGLER	5.24	6.79	33
FRANKLIN	-4.27	2.54	7
FSU LAB SCH	8.41	3.87	9
GADSDEN	-6.52	9.50	18
GILCHRIST	1.78	2.41	15
GLADES	-4.79	3.79	5
GULF	*	*	3
HAMILTON	-4.54	3.12	9
HARDEE	-3.85	5.04	11
HENDRY	-7.56	4.05	19
HERNANDO	3.96	6.36	67
HIGHLANDS	-1.18	5.49	29
HILLSBOROUGH	-3.76	7.50	450
HOLMES	-3.15	8.36	15
INDIAN RIVER	4.22	6.77	34
JACKSON	3.30	6.80	23
JEFFERSON	4.37	0.91	7

District	Reading		
	Mean	Std. Dev.	N
LAFAYETTE	*	*	3
LAKE	1.03	6.69	78
LEE	-1.29	7.52	155
LEON	3.69	6.52	83
LEVY	3.44	4.64	23
LIBERTY	-5.72	5.07	8
MADISON	2.06	2.21	11
MANATEE	2.30	11.40	116
MARION	5.07	7.83	118
MARTIN	-2.52	9.97	31
MONROE	-2.60	6.23	24
NASSAU	3.35	7.24	22
OKALOOSA	2.10	10.49	73
OKEECHOBEE	-7.04	6.94	15
ORANGE	-0.49	7.95	312
OSCEOLA	0.38	6.02	144
PALM BEACH	-1.19	9.21	408
PASCO	2.30	5.87	214
PINELLAS	-0.47	6.24	233
POLK	-2.75	7.37	237
PUTNAM	4.35	7.11	25
SANTA ROSA	9.28	8.09	53
SARASOTA	2.06	7.12	99
SEMINOLE	-2.30	6.65	160
ST. JOHNS	12.38	9.61	75
ST. LUCIE	-3.35	7.52	83
SUMTER	3.01	5.51	18
SUWANNEE	4.04	6.50	14
TAYLOR	-0.91	3.17	6
UF LAB SCH	*	*	2
UNION	-4.47	3.15	11
VOLUSIA	2.64	8.69	177
WAKULLA	11.26	4.88	16
WALTON	2.15	6.88	31
WASHINGTON	1.85	8.08	9
State Avg.	-0.14	8.47	6256

Table 7. Mean and Standard Deviation of Teacher Value-Added Scores by District: Grade 10, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	1.72	5.48	70	-0.14	29.47	76
BAKER	-5.78	2.59	11	6.05	23.16	13
BAY	-0.85	6.36	89	-9.51	28.35	80
BRADFORD	-1.04	2.65	10	4.55	37.65	13
BREVARD	1.80	5.77	193	-4.53	25.91	206
BROWARD	-4.59	5.93	690	5.54	31.12	753
CALHOUN	3.19	3.86	7	8.97	22.86	13
CHARLOTTE	-2.72	5.29	47	-8.34	23.50	50
CITRUS	-0.39	6.19	58	-6.01	23.15	54
CLAY	2.10	5.08	104	2.49	20.12	138
COLLIER	3.94	6.42	120	-1.50	30.01	142
COLUMBIA	3.86	4.48	7	-4.26	15.78	10
DADE	1.49	7.03	894	16.61	32.44	1058
DEAF/BLIND	8.42	5.55	9	-15.10	18.94	10
DESOTO	-2.40	5.72	16	-3.32	25.41	25
DIXIE	*	*	4	12.99	17.03	6
DOZIER/OKEEC	*	*	4	*	*	4
DUVAL	-4.52	6.40	328	1.38	29.15	434
ESCAMBIA	0.51	5.80	111	-7.55	25.09	167
FAMU LAB SCH	*	*	1	10.87	18.09	5
FLAGLER	-0.92	6.75	34	6.29	31.34	33
FRANKLIN	-7.59	4.77	7	-20.12	20.04	6
FSU LAB SCH	2.15	6.81	5	19.08	19.46	6
GADSDEN	1.79	8.92	16	-11.05	23.88	21
GILCHRIST	2.19	3.49	8	4.94	22.95	13
GLADES	*	*	4	23.05	21.39	6
GULF	2.63	4.59	8	7.05	34.28	7
HAMILTON	-1.20	2.88	7	0.78	17.88	8
HARDEE	7.75	6.44	10	8.60	25.12	16
HENDRY	-0.38	7.40	22	-7.07	24.52	32
HERNANDO	0.83	5.20	79	-1.14	24.48	92
HIGHLANDS	-0.62	4.79	28	-4.87	24.82	39
HILLSBOROUGH	0.54	5.69	483	-2.66	31.21	631
HOLMES	-3.58	8.05	9	-11.01	17.48	18
INDIAN RIVER	-2.51	5.21	40	-4.65	19.48	47
JACKSON	0.75	6.15	24	-0.63	19.62	28
JEFFERSON	2.18	1.77	6	-8.20	22.46	9
LAFAYETTE	*	*	3	*	*	4
LAKE	-4.48	6.37	107	-0.53	29.30	132

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LEE	1.38	5.83	209	3.79	27.75	237
LEON	-0.37	4.93	94	-0.35	24.86	88
LEVY	-1.70	5.64	23	-10.82	25.40	28
LIBERTY	1.14	4.07	6	-9.71	16.30	10
MADISON	3.85	5.49	9	-23.50	17.98	17
MANATEE	0.66	6.14	102	-2.46	26.42	123
MARION	-0.45	5.93	114	-5.30	24.99	132
MARTIN	-0.46	5.79	51	-1.59	25.94	57
MONROE	1.95	4.79	28	6.08	19.94	39
NASSAU	-1.66	4.03	33	-12.08	25.98	33
OKALOOSA	-0.19	5.83	71	-2.44	27.74	81
OKEECHOBEE	-0.87	4.38	18	0.75	36.99	21
ORANGE	-1.00	5.92	399	0.62	27.81	436
OSCEOLA	5.16	5.89	161	13.64	23.61	204
PALM BEACH	-0.31	6.25	471	7.54	26.15	579
PASCO	1.79	5.60	201	-3.34	22.26	255
PINELLAS	0.36	5.86	336	0.95	26.76	348
POLK	-0.01	5.71	271	-9.07	27.00	323
PUTNAM	-0.67	5.62	30	-2.73	23.44	30
SANTA ROSA	-2.26	4.83	67	1.33	21.54	68
SARASOTA	1.09	5.85	119	-1.49	28.15	119
SEMINOLE	3.83	6.57	186	0.75	26.02	190
ST. JOHNS	4.40	5.41	112	1.61	24.62	99
ST. LUCIE	0.42	6.66	90	1.77	27.15	112
SUMTER	-0.54	4.52	20	1.19	22.34	23
SUWANNEE	-0.01	4.19	20	7.20	26.09	17
TAYLOR	-4.59	4.91	8	-6.34	20.89	10
UF LAB SCH	*	*	3	*	*	3
UNION	-4.75	4.88	8	-16.00	23.67	12
VOLUSIA	1.44	6.57	202	-6.51	30.38	228
WAKULLA	-0.15	5.90	12	3.66	20.38	16
WALTON	1.14	6.16	26	-7.43	18.89	35
WASHINGTON	-1.02	11.96	12	-14.65	22.63	17
State Avg.	-0.00	6.56	7160	2.15	28.95	8359

APPENDIX E. SCHOOL COMPONENT BY DISTRICT

Table 1. Mean and Standard Deviation of the School Component by District: Grade 4, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	-4.65	35.85	32	0.11	19.57	31
BAKER	-19.15	NA	1	-34.64	NA	1
BAY	-9.64	47.31	24	3.17	21.81	24
BRADFORD	-21.71	19.17	5	-12.94	10.86	5
BREVARD	3.65	33.11	69	4.02	15.25	69
BROWARD	9.91	33.49	180	0.68	19.28	180
CALHOUN	-2.78	13.88	3	-4.99	16.27	3
CHARLOTTE	-11.89	23.80	10	6.19	24.32	10
CITRUS	22.87	34.91	13	5.41	25.14	13
CLAY	-5.07	27.70	27	-4.21	16.24	27
COLLIER	-8.74	34.32	32	-1.33	19.12	32
COLUMBIA	0.23	31.90	10	-0.27	6.91	10
DADE	3.48	34.10	255	5.41	22.21	255
DEAF/BLIND	*	*	2	*	*	2
DESOTO	5.18	9.42	3	-12.81	6.35	3
DIXIE	10.40	17.86	2	-6.74	3.80	2
DUVAL	15.64	33.18	111	-6.20	19.65	111
ESCAMBIA	-3.71	42.06	39	-4.71	22.61	39
FAMU LAB SCH	*	*	1	*	*	1
FAU LAB SCH	14.85	5.16	2	4.86	26.40	2
FL VIRTUAL	*	*	1	*	*	1
FLAGLER	-29.02	27.14	8	-5.47	13.29	9
FRANKLIN	-11.93	23.43	2	-14.17	18.87	2
FSU LAB SCH	48.82	13.97	2	33.88	2.77	2
GADSDEN	32.44	29.61	11	-0.58	17.09	11
GILCHRIST	30.09	13.38	2	16.37	7.88	2
GLADES	-12.77	4.77	3	-3.51	9.56	3
GULF	40.56	2.49	2	4.95	33.38	2
HAMILTON	5.86	27.12	3	-1.73	11.85	3
HARDEE	8.42	20.03	5	-11.98	13.84	5
HENDRY	12.91	30.52	6	-2.13	19.82	6
HERNANDO	-15.43	23.07	12	-4.74	20.52	12
HIGHLANDS	-9.39	41.74	9	-2.69	21.39	9
HILLSBOROUGH	-6.47	32.27	161	2.80	18.37	161
HOLMES	23.02	18.70	4	-1.88	16.92	4
INDIAN RIVER	4.31	25.01	17	1.61	12.58	17

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
JACKSON	24.48	34.71	8	12.50	15.77	8
JEFFERSON	13.22	8.88	2	44.33	51.99	2
LAFAYETTE	*	*	1	-11.15	NA	1
LAKE	-6.52	38.69	30	-6.25	15.61	30
LEE	5.60	28.04	60	-0.34	17.33	61
LEON	0.40	28.66	27	-2.39	18.12	27
LEVY	-6.04	15.42	6	-12.02	12.21	6
LIBERTY	-0.14	36.29	2	-4.41	1.67	2
MADISON	-35.80	50.37	4	-3.64	17.33	4
MANATEE	5.31	32.10	43	-0.13	17.37	43
MARION	0.89	27.00	34	-8.68	15.89	35
MARTIN	17.93	24.11	13	-1.82	22.78	13
MONROE	22.47	30.23	11	-10.06	17.45	11
NASSAU	12.80	35.01	6	8.52	11.07	6
OKALOOSA	-10.85	19.84	25	-2.30	15.96	25
OKEECHOBEE	2.54	18.32	6	-5.17	21.51	6
ORANGE	-1.38	32.95	137	-2.73	17.93	137
OSCEOLA	-2.51	23.67	34	6.05	15.84	34
PALM BEACH	3.13	29.88	123	9.48	19.83	123
PASCO	-10.91	28.86	52	-9.37	18.13	52
PINELLAS	-14.80	30.93	85	-2.13	14.71	84
POLK	-11.17	32.82	84	-5.38	20.46	84
PUTNAM	23.05	36.33	11	5.45	16.63	11
SANTA ROSA	-5.96	31.90	14	3.19	18.83	14
SARASOTA	-16.26	32.42	33	2.16	17.42	33
SEMINOLE	4.39	27.28	40	0.65	17.24	40
ST. JOHNS	-8.56	35.13	19	9.69	22.05	19
ST. LUCIE	-2.41	29.65	30	-14.97	20.76	30
SUMTER	13.88	12.39	5	11.77	27.69	5
SUWANNEE	1.28	24.17	3	-5.05	11.49	3
TAYLOR	-25.60	6.92	2	-0.85	4.54	2
UF LAB SCH	*	*	1	*	*	1
UNION	44.10	NA	1	24.30	NA	1
VOLUSIA	-12.13	27.05	48	-7.33	15.29	48
WAKULLA	-14.55	21.78	5	3.39	19.48	5
WALTON	11.74	8.35	7	6.55	7.00	7
WASHINGTON	16.32	48.80	2	0.53	19.65	2
State Avg.	0.16	33.02	2,083	0.02	19.43	2,084

Table 2. Mean and Standard Deviation of the School Component by District: Grade 5, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	1.75	26.82	31	0.75	16.33	31
BAKER	-39.24	NA	1	-36.86	NA	1
BAY	-0.74	28.99	24	1.48	12.63	24
BRADFORD	-7.01	18.27	5	-3.00	9.76	5
BREVARD	-0.54	23.31	69	-3.21	13.43	69
BROWARD	5.26	26.33	178	-1.87	16.98	178
CALHOUN	3.13	26.95	3	-11.08	9.00	3
CHARLOTTE	-0.35	18.42	12	8.48	14.98	11
CITRUS	8.17	17.36	12	5.91	13.46	12
CLAY	-0.35	24.64	27	-3.33	14.68	27
COLLIER	-10.75	22.24	34	-9.63	12.59	34
COLUMBIA	1.66	9.05	8	3.67	7.19	8
DADE	-1.96	25.99	255	4.03	17.17	254
DEAF/BLIND	*	*	2	*	*	2
DESOTO	-1.16	5.07	3	-27.99	7.70	3
DIXIE	*	*	2	17.29	17.70	2
DUVAL	0.94	24.18	112	-2.03	15.10	112
ESCAMBIA	-5.80	27.01	39	-0.78	18.08	39
FAMU LAB SCH	*	*	1	*	*	1
FAU LAB SCH	9.91	29.77	2	-0.92	22.42	2
FL VIRTUAL	*	*	1	*	*	*
FLAGLER	-10.12	25.44	8	5.60	7.31	8
FRANKLIN	*	*	2	-1.22	3.62	2
FSU LAB SCH	1.58	27.27	2	2.54	1.81	2
GADSDEN	15.51	28.06	10	4.41	33.40	10
GILCHRIST	-19.43	54.69	2	12.67	23.33	2
GLADES	-5.78	6.63	3	-16.67	18.92	3
GULF	-18.19	1.55	2	-4.27	24.28	2
HAMILTON	-1.14	17.60	3	-4.11	9.69	3
HARDEE	-6.36	23.75	5	-14.37	9.28	5
HENDRY	3.62	41.63	6	0.73	7.02	6
HERNANDO	-17.95	16.93	13	-4.81	13.88	13
HIGHLANDS	-21.62	26.63	9	-8.03	18.78	9
HILLSBOROUGH	-1.99	21.37	165	1.37	13.56	165
HOLMES	-11.32	28.68	4	3.87	10.31	4
INDIAN RIVER	12.50	20.10	16	-3.50	9.45	16
JACKSON	-20.02	29.41	8	-0.74	11.51	8
JEFFERSON	34.11	33.19	2	15.44	20.10	2
LAFAYETTE	*	*	1	-0.53	NA	1

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LAKE	-2.63	21.39	30	-0.70	13.94	30
LEE	14.15	23.75	59	-6.44	13.10	60
LEON	3.71	28.86	27	7.03	23.61	27
LEVY	-14.58	21.24	7	-3.07	10.15	7
LIBERTY	-7.39	19.76	2	25.55	6.25	2
MADISON	-19.96	26.47	4	5.39	14.40	4
MANATEE	8.93	22.25	42	-1.60	10.92	42
MARION	0.80	19.83	35	-5.08	14.65	35
MARTIN	11.48	25.17	12	-1.00	10.04	12
MONROE	2.30	14.76	11	-4.42	9.38	11
NASSAU	4.42	12.39	6	-3.47	12.91	5
OKALOOSA	0.98	18.38	24	-1.13	10.34	24
OKEECHOBEE	9.68	46.51	5	-12.88	22.69	5
ORANGE	2.35	25.52	138	1.92	14.22	138
OSCEOLA	8.97	19.94	34	3.36	15.35	34
PALM BEACH	-1.49	19.82	123	3.77	14.91	123
PASCO	2.05	23.65	55	-2.99	13.95	52
PINELLAS	-7.87	27.21	88	-2.07	13.37	86
POLK	-8.51	28.63	85	-1.59	16.03	85
PUTNAM	9.34	22.17	10	-2.27	15.93	10
SANTA ROSA	-3.93	26.79	15	5.03	17.30	15
SARASOTA	1.83	22.35	33	6.28	14.81	33
SEMINOLE	4.92	22.15	40	3.23	13.76	40
ST. JOHNS	5.90	15.99	21	13.21	12.65	20
ST. LUCIE	5.89	29.11	30	-0.19	13.13	30
SUMTER	16.09	15.03	6	14.67	12.92	5
SUWANNEE	15.96	13.96	2	3.43	8.21	2
TAYLOR	-30.04	10.69	2	-9.68	11.88	2
UF LAB SCH	*	*	1	*	*	1
UNION	-17.10	NA	1	-19.43	NA	1
VOLUSIA	-5.63	20.69	48	-8.72	13.04	48
WAKULLA	2.84	17.83	5	3.20	19.47	5
WALTON	20.40	15.02	7	5.45	10.63	7
WASHINGTON	-75.58	25.39	2	-9.26	15.87	2
State Avg.	0.04	24.78	2,092	0.02	15.49	2,082

Table 3. Mean and Standard Deviation of the School Component by District: Grade 6, 2010-11

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	-8.12	34.52	16	-9.09	18.94	17
BAKER	89.28	NA	1	4.41	NA	1
BAY	-6.47	24.52	13	-9.53	18.99	13
BRADFORD	0.15	46.23	3	-4.68	9.43	3
BREVARD	50.92	38.80	70	11.49	19.39	70
BROWARD	-2.09	25.64	78	2.28	20.41	79
CALHOUN	13.20	27.24	3	-4.18	17.68	3
CHARLOTTE	-13.20	20.75	6	0.45	21.43	6
CITRUS	-10.92	18.60	6	-22.02	15.84	6
CLAY	28.92	26.45	25	6.43	16.57	25
COLLIER	16.03	23.38	21	10.86	16.35	21
COLUMBIA	-15.09	7.27	3	-19.30	2.63	3
DADE	-12.20	36.56	140	11.98	24.98	144
DEAF/BLIND	*	*	2	*	*	2
DESOTO	-4.53	25.04	3	-19.62	29.76	2
DIXIE	*	*	1	28.74	NA	1
DUVAL	-21.47	31.90	39	-8.00	20.97	40
ESCAMBIA	-19.67	25.06	15	-17.88	21.13	15
FAMU LAB SCH	*	*	1	*	*	1
FAU LAB SCH	29.18	40.24	2	44.43	29.59	2
FL VIRTUAL	*	*	1	*	*	1
FLAGLER	9.44	19.68	8	6.27	15.25	8
FRANKLIN	-23.70	37.51	2	-4.81	14.42	2
FSU LAB SCH	*	*	1	*	*	1
GADSDEN	-1.64	40.85	8	-19.21	32.75	8
GILCHRIST	*	*	2	-6.99	5.07	2
GLADES	*	*	3	-3.10	27.52	3
GULF	-39.71	21.38	2	-3.03	9.46	2
HAMILTON	55.42	55.85	4	-13.39	13.04	4
HARDEE	-18.49	5.72	2	-4.76	3.64	2
HENDRY	-30.58	8.39	3	-26.99	13.31	3
HERNANDO	-6.73	22.48	10	-4.94	16.94	10
HIGHLANDS	15.73	32.13	6	7.17	16.58	5
HILLSBOROUGH	-0.24	25.41	71	-15.57	21.58	70
HOLMES	28.46	33.72	5	-5.61	11.18	5
INDIAN RIVER	7.32	18.47	7	-4.24	16.71	7
JACKSON	-17.79	8.97	7	-5.82	13.69	6
JEFFERSON	-0.65	2.92	3	0.46	4.84	2
LAFAYETTE	*	*	1	*	*	1

District	Mathematics			Reading		
	Mean	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
LAKE	-4.19	24.16	16	-1.81	20.13	16
LEE	-6.80	25.74	33	-11.17	19.54	35
LEON	2.58	27.02	18	-0.51	19.25	19
LEVY	2.57	23.29	8	-7.88	17.91	8
LIBERTY	22.71	41.88	3	*	*	3
MADISON	-16.24	0.76	2	-18.46	13.03	2
MANATEE	-10.22	24.94	23	-2.98	15.30	24
MARION	-11.97	17.60	15	1.23	13.72	15
MARTIN	4.84	21.60	6	-3.57	9.43	6
MONROE	20.74	21.99	8	15.11	9.51	8
NASSAU	0.64	9.53	5	-13.06	12.21	5
OKALOOSA	8.31	25.13	17	2.76	11.95	17
OKEECHOBEE	13.90	4.86	2	-5.85	6.19	3
ORANGE	-4.97	24.06	55	2.98	16.30	57
OSCEOLA	2.42	23.80	21	12.88	16.05	21
PALM BEACH	2.90	28.50	54	4.77	22.10	54
PASCO	12.65	30.14	22	-0.91	18.46	22
PINELLAS	-19.35	23.57	33	-17.03	16.96	33
POLK	-19.54	30.40	41	-3.81	16.07	42
PUTNAM	1.78	55.11	6	-25.71	26.98	6
SANTA ROSA	-8.57	20.73	13	-0.40	12.86	13
SARASOTA	9.57	30.53	18	13.37	21.20	18
SEMINOLE	-5.28	16.40	15	8.68	12.83	15
ST. JOHNS	3.96	41.76	10	12.06	28.99	10
ST. LUCIE	5.57	25.59	20	3.47	13.76	20
SUMTER	-12.66	41.06	5	-11.59	22.39	5
SUWANNEE	-9.63	4.40	4	1.68	3.96	4
TAYLOR	-3.84	5.41	2	14.52	2.40	2
UF LAB SCH	*	*	1	*	*	1
UNION	-12.10	NA	1	20.78	NA	1
VOLUSIA	-15.48	25.54	20	-18.16	11.97	20
WAKULLA	13.86	14.11	4	-14.37	10.96	4
WALTON	36.99	24.16	5	8.84	21.43	5
WASHINGTON	-13.11	0.20	2	-8.01	24.08	2
State Avg.	0.14	33.70	1,102	0.03	21.63	1,112

Table 4. Mean and Standard Deviation of the School Component by District: Grade 7, 2010-11

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	0.32	9.63	20	-4.18	8.91	19
BAKER	-14.96	NA	1	11.95	NA	1
BAY	1.39	13.31	13	-1.94	8.92	14
BRADFORD	0.13	1.37	2	-9.53	12.44	2
BREVARD	-11.34	12.01	29	-10.60	12.88	29
BROWARD	-3.04	12.17	77	-2.93	15.86	79
CALHOUN	0.03	10.13	3	-22.39	14.93	3
CHARLOTTE	6.16	13.80	6	8.90	13.28	6
CITRUS	2.54	15.70	7	-14.65	12.38	7
CLAY	-7.57	12.48	8	1.49	11.60	8
COLLIER	6.45	11.65	17	3.33	13.76	18
COLUMBIA	-9.96	9.36	3	-0.05	6.30	3
DADE	-0.54	12.76	141	10.84	16.20	141
DEAF/BLIND	*	*	2	*	*	2
DESOTO	-1.95	4.35	4	2.32	6.10	4
DIXIE	-5.36	NA	1	14.03	NA	1
DUVAL	2.01	12.48	45	2.18	12.32	46
ESCAMBIA	-3.74	8.97	15	-13.66	15.51	15
FAMU LAB SCH	*	*	1	*	*	1
FAU LAB SCH	-1.79	4.74	2	2.26	2.00	2
FL VIRTUAL	*	*	1	*	*	1
FLAGLER	0.24	12.66	5	-4.18	8.03	5
FRANKLIN	*	*	2	4.79	14.86	2
FSU LAB SCH	*	*	1	*	*	1
GADSDEN	-7.78	9.72	6	-4.24	18.39	6
GILCHRIST	*	*	2	-17.51	9.54	2
GLADES	*	*	3	-16.98	8.54	3
GULF	6.22	6.90	2	-2.72	21.83	2
HAMILTON	*	*	2	-8.47	4.68	2
HARDEE	-18.56	NA	1	3.46	NA	1
HENDRY	-4.60	11.38	3	-11.50	21.53	3
HERNANDO	3.28	8.17	10	4.59	5.31	10
HIGHLANDS	8.74	9.32	6	5.82	13.45	6
HILLSBOROUGH	2.97	13.40	74	-5.25	12.85	75
HOLMES	-1.49	12.58	5	-15.12	15.71	6
INDIAN RIVER	4.66	10.42	7	-11.78	21.58	7
JACKSON	-2.55	7.92	8	-10.29	18.16	7
JEFFERSON	-7.19	14.39	2	-0.68	0.43	2
LAFAYETTE	*	*	1	*	*	1

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LAKE	-0.02	12.78	15	0.11	11.96	15
LEE	7.28	13.99	33	-1.66	15.92	33
LEON	-0.94	14.45	20	-1.88	21.06	20
LEVY	2.33	12.71	8	-3.57	20.00	8
LIBERTY	1.59	14.61	4	-10.79	11.50	4
MADISON	2.48	3.00	3	3.76	8.76	3
MANATEE	1.31	11.45	25	0.66	11.79	25
MARION	-3.09	9.30	15	7.32	12.11	15
MARTIN	1.21	10.17	6	-17.55	4.61	6
MONROE	2.25	10.10	7	-0.24	8.82	7
NASSAU	-0.55	13.89	5	3.88	12.17	5
OKALOOSA	1.02	13.24	17	2.79	11.83	18
OKEECHOBEE	0.59	9.59	4	-9.09	16.75	3
ORANGE	4.00	13.14	54	6.48	14.55	55
OSCEOLA	4.13	11.49	20	5.31	13.95	20
PALM BEACH	-0.83	13.46	54	3.16	16.44	54
PASCO	4.82	9.65	26	4.51	10.04	26
PINELLAS	-8.70	11.16	36	-2.57	15.92	37
POLK	-4.74	9.45	43	-6.58	16.73	42
PUTNAM	-5.64	6.98	6	4.44	13.20	6
SANTA ROSA	-2.67	8.08	12	1.28	16.60	12
SARASOTA	1.36	12.46	20	5.08	14.51	20
SEMINOLE	5.18	13.57	17	-0.20	13.01	17
ST. JOHNS	5.62	11.83	13	9.45	18.30	14
ST. LUCIE	1.14	10.88	19	-10.58	14.28	19
SUMTER	1.38	8.65	6	-11.52	23.45	6
SUWANNEE	1.15	4.44	4	0.72	6.00	4
TAYLOR	-1.39	11.12	2	-9.52	20.21	2
UF LAB SCH	*	*	1	*	*	1
UNION	3.85	NA	1	24.84	16.37	2
VOLUSIA	-4.13	9.32	23	-17.04	12.98	23
WAKULLA	6.75	9.90	4	-12.24	15.96	4
WALTON	7.86	14.10	8	6.02	13.78	8
WASHINGTON	0.88	3.99	2	-4.41	9.95	3
State Avg.	-0.02	12.38	1,071	0.00	16.01	1,080

Table 5. Mean and Standard Deviation of School the School Component by District: Grade 8, 2010-11

	Mathematics			Reading		
District	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	5.43	10.21	21	0.75	8.03	19
BAKER	-18.66	NA	1	-1.59	NA	1
BAY	-1.92	13.73	13	-0.87	6.97	14
BRADFORD	0.72	7.85	3	1.74	6.33	2
BREVARD	-7.21	7.96	30	-5.37	6.91	29
BROWARD	0.85	11.19	74	2.97	12.18	74
CALHOUN	5.22	9.13	3	-8.75	5.64	3
CHARLOTTE	0.95	7.76	6	6.96	9.86	6
CITRUS	1.91	3.99	8	-5.49	15.52	6
CLAY	-0.07	11.82	11	-0.54	4.41	10
COLLIER	5.90	10.82	20	1.32	11.23	19
COLUMBIA	-2.38	2.12	4	-5.44	8.49	4
DADE	1.98	12.33	141	7.74	12.97	141
DEAF/BLIND	*	*	2	-1.49	13.30	2
DESOTO	-5.73	3.57	4	-3.37	4.77	5
DIXIE	*	*	1	3.65	NA	1
DOZIER/OKEEC	*	*	1	*	*	1
DUVAL	-0.37	10.19	41	4.02	9.71	42
ESCAMBIA	-4.43	10.06	16	-7.31	10.57	17
FAMU LAB SCH	*	*	1	*	*	1
FAU LAB SCH	3.67	1.20	2	9.79	11.39	2
FL VIRTUAL	*	*	2	*	*	2
FLAGLER	-3.76	6.78	6	-1.35	9.21	6
FRANKLIN	-9.97	3.02	2	-7.28	7.83	2
FSU LAB SCH	*	*	1	6.73	NA	1
GADSDEN	2.26	11.88	6	0.73	20.63	6
GILCHRIST	*	*	2	-12.37	1.00	2
GLADES	*	*	2	-13.15	3.10	2
GULF	3.02	0.02	2	-13.77	1.60	2
HAMILTON	-14.20	4.93	2	-4.60	24.46	2
HARDEE	2.26	7.69	2	-9.53	3.51	2
HENDRY	-1.12	8.03	4	-10.81	18.27	4
HERNANDO	-2.07	10.58	10	-3.17	11.54	10
HIGHLANDS	-0.26	8.87	8	-1.44	7.75	6
HILLSBOROUGH	-3.77	9.01	76	-5.29	11.10	77
HOLMES	-2.10	8.57	6	-4.70	7.71	5
INDIAN RIVER	-5.87	10.07	6	-9.97	9.63	7
JACKSON	-3.83	8.68	7	-6.60	3.54	6
JEFFERSON	*	*	1	*	*	1

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LAFAYETTE	*	*	1	*	*	1
LAKE	0.64	7.66	15	-0.13	7.89	15
LEE	6.81	14.96	34	-1.25	11.57	34
LEON	1.81	9.44	22	1.40	11.08	22
LEVY	0.36	8.52	8	1.85	13.82	8
LIBERTY	-8.87	4.03	3	-0.52	2.68	5
MADISON	-1.49	4.13	3	-16.33	15.10	3
MANATEE	0.12	9.10	24	-5.62	7.22	24
MARION	0.64	11.51	15	-1.75	9.97	15
MARTIN	3.39	7.04	7	0.09	6.11	7
MONROE	13.47	12.90	7	1.19	10.20	6
NASSAU	-9.90	12.28	5	3.61	5.95	7
OKALOOSA	1.20	11.88	20	6.73	11.62	18
OKEECHOBEE	-5.00	15.80	3	-11.71	4.47	3
ORANGE	-3.98	11.96	60	1.86	11.56	58
OSCEOLA	3.49	9.59	20	-2.62	11.34	20
PALM BEACH	4.59	12.59	57	5.49	10.91	53
PASCO	0.30	11.31	36	-0.21	9.57	26
PINELLAS	-7.39	8.65	37	-4.79	10.28	37
POLK	-1.52	8.50	42	-6.11	13.70	43
PUTNAM	-4.61	6.10	8	5.76	5.33	6
SANTA ROSA	-0.69	12.66	11	3.94	10.46	13
SARASOTA	5.08	12.24	21	1.00	8.11	20
SEMINOLE	4.68	11.22	17	1.83	11.49	17
ST. JOHNS	1.71	11.08	17	8.17	12.28	17
ST. LUCIE	3.20	11.33	19	-6.64	13.41	19
SUMTER	-3.98	5.05	5	-10.20	6.56	5
SUWANNEE	-6.75	2.58	5	-1.60	3.52	5
TAYLOR	2.96	7.18	2	2.31	2.00	2
UF LAB SCH	*	*	1	*	*	1
UNION	3.54	NA	1	-4.83	3.77	2
VOLUSIA	-3.26	9.28	25	-13.83	11.10	25
WAKULLA	-1.43	7.12	4	-6.93	4.33	4
WALTON	5.27	12.25	8	3.69	12.98	8
WASHINGTON	8.56	12.42	3	-3.66	9.96	3
State Avg.	0.05	11.19	1,114	0.03	12.07	1,094

Table 6. Mean and Standard Deviation of School the School Component by District: Grade 9, 2010-11

District	Reading		
	Mean	Std. Dev.	N
ALACHUA	7.44	10.83	14
BAKER	19.53	NA	1
BAY	2.32	9.71	14
BRADFORD	3.51	6.70	2
BREVARD	6.40	10.29	24
BROWARD	-9.13	12.11	60
CALHOUN	-8.32	3.74	2
CHARLOTTE	5.38	7.46	7
CITRUS	6.35	10.82	10
CLAY	6.64	7.97	9
COLLIER	0.08	10.11	16
COLUMBIA	-0.48	1.16	2
DADE	-0.71	9.20	99
DEAF/BLIND	2.30	5.62	2
DESOTO	-2.18	4.47	6
DIXIE	*	*	1
DOZIER/OKEEC	-2.52	7.05	2
DUVAL	0.91	8.09	37
ESCAMBIA	-3.51	8.58	17
FAMU LAB SCH	*	*	1
FAU LAB SCH	*	*	1
FL VIRTUAL	*	*	1
FLAGLER	5.18	7.36	4
FRANKLIN	-4.64	4.18	2
FSU LAB SCH	14.71	NA	1
GADSDEN	-6.58	12.76	5
GILCHRIST	2.97	1.13	2
GLADES	-7.68	NA	1
GULF	*	*	2
HAMILTON	-4.52	8.12	2
HARDEE	-6.91	NA	1
HENDRY	-8.90	5.52	4
HERNANDO	5.57	7.49	8
HIGHLANDS	0.83	7.66	6
HILLSBOROUGH	-4.12	9.52	53
HOLMES	-2.48	10.59	6
INDIAN RIVER	5.23	7.85	5
JACKSON	4.47	10.45	7
JEFFERSON	7.33	NA	1

District	Reading		
	Mean	Std. Dev.	N
LAFAYETTE	*	*	1
LAKE	1.59	7.60	13
LEE	0.60	10.21	25
LEON	3.74	7.79	15
LEVY	5.90	6.83	6
LIBERTY	-4.70	6.24	4
MADISON	2.15	3.81	3
MANATEE	-0.81	17.52	13
MARION	4.43	11.35	14
MARTIN	-2.89	11.36	5
MONROE	0.02	9.03	4
NASSAU	4.75	7.75	6
OKALOOSA	2.02	12.55	16
OKEECHOBEE	-8.84	10.55	3
ORANGE	-0.91	9.71	48
OSCEOLA	-0.67	7.86	17
PALM BEACH	-0.71	12.41	48
PASCO	3.13	7.59	21
PINELLAS	-1.02	5.52	38
POLK	-1.92	9.46	33
PUTNAM	4.10	11.40	5
SANTA ROSA	6.96	12.87	11
SARASOTA	4.38	10.03	13
SEMINOLE	-4.39	8.27	14
ST. JOHNS	14.46	17.43	12
ST. LUCIE	-2.66	10.94	14
SUMTER	2.53	7.43	5
SUWANNEE	2.54	10.22	3
TAYLOR	-2.16	0.76	2
UF LAB SCH	*	*	1
UNION	-4.85	5.02	2
VOLUSIA	1.11	12.46	25
WAKULLA	10.04	17.74	2
WALTON	1.01	10.27	6
WASHINGTON	3.37	11.59	3
State Avg.	0.04	10.64	889

Table 7. Mean and Standard Deviation of the School Component by District: Grade 10, 2010-11

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
ALACHUA	1.32	3.96	11	-1.49	15.05	12
BAKER	-9.33	NA	1	7.63	NA	1
BAY	-0.68	6.20	11	-8.58	12.20	11
BRADFORD	-1.06	0.95	2	3.33	0.19	2
BREVARD	2.03	4.87	24	-4.62	11.55	23
BROWARD	-6.18	6.25	58	3.84	16.87	59
CALHOUN	3.82	0.60	2	7.11	4.93	2
CHARLOTTE	-2.04	5.19	7	-6.11	9.66	8
CITRUS	0.01	3.37	8	-4.93	7.43	9
CLAY	1.97	4.59	10	2.31	7.99	9
COLLIER	3.05	6.56	18	-3.94	13.30	17
COLUMBIA	4.58	5.33	2	-2.82	1.66	2
DADE	2.57	7.86	92	13.45	19.89	92
DEAF/BLIND	11.14	7.38	2	-13.82	3.45	2
DESOTO	-1.10	4.89	5	-0.57	12.08	4
DIXIE	*	*	1	4.67	8.36	2
DOZIER/OKEEC	*	*	2	*	*	2
DUVAL	-4.96	7.09	35	-0.36	15.59	38
ESCAMBIA	0.05	3.08	17	-7.47	10.84	17
FAMU LAB SCH	*	*	1	1.21	NA	1
FLAGLER	-3.24	6.89	5	2.81	16.80	5
FRANKLIN	-6.60	8.42	2	-10.07	9.83	2
FSU LAB SCH	2.95	NA	1	16.82	NA	1
GADSDEN	3.44	12.19	4	-7.32	8.08	4
GILCHRIST	2.88	4.13	2	4.20	13.00	2
GLADES	*	*	1	16.99	NA	1
GULF	3.41	5.96	2	4.98	16.92	2
HAMILTON	-1.04	2.34	2	1.61	1.01	2
HARDEE	12.62	NA	1	11.66	NA	1
HENDRY	-0.15	4.83	4	-8.46	16.90	4
HERNANDO	0.13	7.18	7	-3.98	11.82	7
HIGHLANDS	1.08	4.17	5	-5.53	6.23	6
HILLSBOROUGH	0.67	4.73	46	-3.58	9.28	61
HOLMES	-2.90	4.94	4	-6.50	8.40	5
INDIAN RIVER	-4.23	1.19	4	-5.15	7.80	4
JACKSON	1.89	4.82	6	-1.20	3.44	7
JEFFERSON	1.81	2.45	2	-4.42	8.22	2
LAFAYETTE	*	*	1	*	*	1
LAKE	-6.18	5.26	11	-2.42	9.68	12

District	Mathematics			Reading		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
LEE	0.47	5.63	30	1.97	15.55	30
LEON	-0.85	3.25	12	-2.10	12.45	13
LEVY	-1.35	2.58	7	-7.42	9.49	6
LIBERTY	0.71	1.21	3	-3.70	5.57	4
MADISON	1.59	6.46	3	-13.75	9.73	4
MANATEE	-1.04	6.23	15	-2.25	8.75	16
MARION	-1.56	5.34	15	-6.91	11.60	15
MARTIN	-1.08	4.01	6	-1.03	9.80	6
MONROE	1.94	3.03	5	5.24	4.39	5
NASSAU	-2.63	1.43	4	-9.52	11.38	5
OKALOOSA	-0.03	3.64	16	-1.93	13.60	17
OKEECHOBEE	-0.19	3.05	3	-0.12	14.23	3
ORANGE	-1.50	5.12	43	-1.82	13.13	44
OSCEOLA	5.13	7.72	19	10.90	14.87	20
PALM BEACH	-0.76	6.29	48	6.13	15.54	48
PASCO	1.85	5.07	20	-3.48	10.15	22
PINELLAS	0.13	4.09	38	-1.18	9.90	38
POLK	0.04	5.29	32	-8.86	10.87	33
PUTNAM	-0.60	3.72	6	-2.72	6.98	5
SANTA ROSA	-3.27	2.10	8	-2.33	12.15	9
SARASOTA	2.22	5.63	13	-1.20	13.02	13
SEMINOLE	5.05	6.63	13	0.00	12.15	14
ST. JOHNS	5.40	5.68	13	0.79	15.14	13
ST. LUCIE	-0.06	4.77	13	1.25	12.20	14
SUMTER	-0.56	1.50	5	0.85	6.14	5
SUWANNEE	0.64	1.75	4	1.46	12.49	4
TAYLOR	-5.94	0.31	2	-2.76	8.02	2
UF LAB SCH	*	*	1	*	*	1
UNION	-3.09	8.89	2	-11.51	6.43	2
VOLUSIA	0.93	5.25	23	-7.60	10.50	26
WAKULLA	0.72	3.44	2	-0.75	12.98	2
WALTON	1.97	6.39	5	-6.03	6.52	6
WASHINGTON	0.07	18.02	2	-10.00	14.08	3
State Avg.	-0.03	6.31	850	0.03	14.49	890

APPENDIX F. EXPECTED STUDENT GROWTH BY STUDENT CHARACTERISTICS GIFTED AND ENGLISH LANGUAGE LEARNER (ELL) STATUS

Table 1. Conditional Estimates of Student Growth in Mathematics, 2010-11

	Gifted		Non-Gifted		
Grade	Expected Growth	N	Expected Growth	N	Difference
4	2.0649064	433	88.476418	175993	-86.41151
5	88.307073	352	94.806761	163861	-6.499688
6	22.395686	265	44.540499	163134	-22.14481
7	61.926867	266	110.13964	158809	-48.21278
8	46.248282	223	84.55398	162877	-38.3057
10	37.537472	189	49.837181	156023	-12.29971
	ELL		**Non-ELL**		
Grade	**Expected Growth**	**N**	**Expected Growth**	**N**	**Difference**
4	153.8212	12649	83.201182	163777	70.620016
5	88.530364	318	94.80498	163895	-6.274616
6	42.75846	194	44.50666	163205	-1.7482
7	163.83582	157	110.0059	158918	53.829926
8	134.31363	162	84.452081	162938	49.86155
10	81.997501	123	49.796945	156089	32.200556

Table 2. Conditional Estimates of Student Growth in Reading, 2010-11

	Gifted		Non-Gifted		
Grade	Expected Growth	N	Expected Growth	N	Difference
4	146.44818	435	184.83559	176048	-38.3874
5	63.433327	349	43.207596	163983	20.225731
6	83.647422	265	84.322599	163500	-0.675177
7	37.421107	273	87.788687	160446	-50.36758
8	12.554883	225	55.417656	163607	-42.86277
9	77.075954	191	45.612021	156303	31.463933
10	29.283435	194	25.894549	175184	3.3888864
	ELL		**Non-ELL**		
Grade	**Expected Growth**	**N**	**Expected Growth**	**N**	**Difference**
4	259.4523	12601	178.99637	163882	80.455937
5	70.388208	318	43.197934	164014	27.190274
6	101.54432	196	84.300869	163569	17.243452
7	118.70982	155	87.673199	160564	31.036619
8	131.12756	161	55.284258	163671	75.843303
9	54.950931	139	45.642154	156355	9.3087774
10	29.830353	143	25.895089	175235	3.9352639

APPENDIX G. TEACHER VALUE-ADDED ESTIMATES BY TEACHER AND CLASSROOM CHARACTERISTICS

Table 1. Correlations between Teacher Value-Added Estimates in Mathematics and Teacher/Classroom Characteristics, by Grade, 2010-11

	Teacher Experience (Years Teaching)		Percent ELLs		Percent Students with a Disability	
Grade	R	N	R	N	R	N
4	0.013535	11475	0.0123558	11734	-0.064932	11734
5	0.0477178	10648	-0.018851	10878	-0.077937	10878
6	0.0506977	4899	-0.015185	5078	-0.044967	5078
7	0.0023436	5212	-0.003385	5425	-0.010703	5425
8	-0.001707	4871	-0.018281	5070	-0.009976	5070
10	0.0436482	6906	-0.010229	7160	0.0002018	7160

Note: a Correlation not statistically significant at the 0.05 level.

Table 2. Average Teacher Value-Added Estimate in Mathematics Conditional on Teacher Education (Highest Degree Completed), by Grade, 2010-11

	Bachelors			Masters			Doctorate		
Grade	M	SD	N	M	SD	N	M	SD	N
4	0.707631	43.309965	7484	2.1478431	42.765888	3769	3.0575055	45.88601	62
5	0.4541213	36.044323	6833	2.2942905	34.878624	3567	-4.908657	33.474936	65
6	-1.323573	27.351898	3216	0.4051395	27.952464	1528	-6.060915	31.297507	47
7	0.2634426	16.903718	3430	0.6566031	16.291611	1619	0.4773194	18.795162	61
8	0.6113125	15.310613	3165	1.4521285	14.901622	1575	-0.332615	19.222769	53
10	-0.101409	6.5856408	4404	0.3717048	6.5016061	2294	-1.296313	6.3220687	90

Table 3. Correlations between Teacher Value-Added Estimates in Reading and Teacher/Classroom Characteristics, by Grade, 2010-11

	Teacher Experience (Years Teaching)		Percent ELLs		Percent Students with a Disability	
Grade	R	N	R	N	R	N
4	0.0748987	12867	0.0105451	13157	-0.043796	13157
5	0.0502077	11921	-0.002441	12182	-0.004587	12182
6	0.0352315	6817	-0.01287	7091	0.0124078	7091
7	0.0152124	6748	0.0073637	7046	-0.010088	7046
8	0.0092342	6350	-0.009317	6633	0.0138814	6633
9	0.0416766	5989	-0.011594	6256	-0.015138	6256
10	0.0474101	8026	0.005232	8359	-0.052846	8359

Note: a Correlation not statistically significant at the 0.05 level.

Table 4. Average Teacher Value-Added Estimate in Reading Conditional on Teacher Education (Highest Degree Completed), by Grade, 2010-11

	Bachelors			Masters			Doctorate		
Grade	M	SD	N	M	SD	N	M	SD	N
4	0.1547858	21.869046	8265	1.5076607	21.267432	4344	3.9394647	19.237942	79
5	-0.188169	17.140617	7630	0.7753865	16.496278	4021	-1.603951	14.136687	75
6	-1.479213	17.02065	4213	0.5371795	16.977228	2366	-0.811501	17.857964	73
7	-0.285201	16.893277	4155	0.9167672	17.644285	2355	2.9334063	19.19087	79
8	-0.270946	11.011726	3877	0.8783048	11.018134	2286	-0.820585	10.177734	64
9	-0.240805	8.4838509	3606	0.3335485	8.5322502	2176	-0.673678	8.8387403	95
10	1.4265224	28.606342	4658	3.3076111	29.425248	3070	1.3153821	27.1821	139